Quantifying Greenhouse Gas Fluxes in Agriculture and Forestry:

METHODS FOR ENTITY-SCALE INVENTORY

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Quantifying Greenhouse Gas Fluxes in Agriculture and Forestry: Methods for Entity-Scale Inventory

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Executive Summary

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Executive Summary

The U.S. Department of Agriculture (USDA) published its first version of *Quantifying Greenhouse Gas Fluxes in Agriculture and Forestry: Methods for Entity-Scale Inventory* in 2014, as directed by Section 2709 of the Food, Conservation, and Energy Act of 2008. In this updated version, USDA has revised the report to reflect the latest science-based methods for estimating greenhouse gas (GHG) emissions and removals from agricultural and forestry activities.

This report has several important purposes, including the following:

- Enables landowners and others to estimate entity-scale GHG fluxes and impacts (including fluxes associated with different management practices) using the most accurate science-based methods currently available.
- Allows USDA to estimate GHG fluxes from current and future conservation programs and practices and assess the performance of conservation and renewable energy programs using the most accurate science-based methods currently available given agency objectives and available resources. Note that the intensity metrics of GHGs (i.e., emissions per production unit) are not explicitly addressed in this guidance.
- Provides a basis for updating USDA's GHG flux estimation tools, including COMET-Planner and COMET-Farm (see box 1-2).
- Informs GHG estimates for other programs. For example, this report may inform emerging methods that underlie voluntary GHG registries, facilitate regional GHG markets, and provide technical inputs for future GHG reporting programs.

This report was developed by authors that have expertise in GHG accounting specific to agriculture and forestry. The authors were chosen based on their experience with GHG inventories and accounting methodologies and their professional research experience. The authors worked in teams under the direction of one lead author for each team (plus one co-lead author for the forestry chapter).

Summary of GHG Flux Sources and Approaches

There are several approaches to GHG emissions estimation at an entity scale, and each approach gives varying accuracy and precision. For some agricultural sectors, direct measurement may be the most accurate way of estimating emissions, however, this often requires expensive equipment or techniques that are not feasible for a single landowner or manager. However, simple lookup tables and estimation equations alone often do not adequately represent local variability or conditions. This report aims to provide methods that balance straightforward approaches, practical data requirements, and appropriate scientific rigor in a way that is transparent and justified.

The authors evaluated updated sources to reflect current science, including the Intergovernmental Panel on Climate Change (IPCC) *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories*. The types of approaches that the authors recommended in this report include multiple levels, or tiers, of complexity and accuracy, based on the best available data and methods, similar to the methodological tiers developed by the IPCC, which are based on the complexity of different approaches for estimating GHG emissions (see box ES-1).

The methods range from the simple Tier 1 approaches to the most complex Tier 3 approaches. Higher-tier methods, particularly Tier 3 methods, are expected to reduce uncertainties in the GHG estimates if sufficient activity data are available and the methods are well developed (Ogle et al., 2019a).

The methods described in this report fall into the following categories:

Box ES-1. IPCC Tiers

- Tier 1 represents the simplest methods, using default equations and emission factors provided in the IPCC guidance.
- Tier 2 uses default methods, but emission factors that are specific to different regions.
- Tier 3 uses country-specific estimation methods, such as a process-based model.

- Basic estimation equations use default equations and emission factors, such as IPCC Tier 1 methods.
- Inference uses geography-, crop-, livestock-, technology-, or practice-specific emission factors to approximate emissions/removal factors. This approach is similar to an IPCC Tier 2 method and is more accurate, more complex, and requires more data inputs than the basic estimation.
- Modified IPCC/empirical and/or process-based modeling, comparable to IPCC Tier 2 or IPCC Tier 3 methods. These methods are the most demanding in terms of complexity and data requirements and produce the most accurate estimates.

Table ES-1 categorizes the GHG flux sources with the types of approaches that are recommended in this report.

Table ES-1: Summary of the Sources of GHG Fluxes and Types of Approaches in This Report

Source	Basic Estimation Equation	Inference	Modified IPCC or Empirical Model	Processed-Based Model
Croplands/Grazing Lands	▪ CH_4 Emissions From Rice Cultivation[a] ▪ CO_2 From Urea Fertilizer Application ▪ Direct N_2O Emissions From Mineral (Other Crops) and Organic Soils[a] ▪ Indirect N_2O Emissions From Mineral Soils ▪ Biomass Carbon Stock Changes (Other Woody) ▪ CH_4 Flux for Organic Soils ▪ Non-CO_2 Emissions From Biomass Burning	▪ Soil Organic Carbon Stocks for Organic Soils ▪ CO_2 From Liming ▪ CH_4 Emissions From Rice Cultivation[a] ▪ Biomass Carbon Stock Changes (Herbaceous)	▪ Biomass Carbon Stock Changes (Woody) ▪ CH_4 Flux for Mineral Soils ▪ Soil Organic Carbon Stocks for Mineral Soils (Other Crops)[a]	▪ Soil Organic Carbon Stocks for Mineral Soils (Most Crops)[a] ▪ Direct N_2O Emissions From Mineral Soils (Most Crops and Grazing Lands)[a]
Animal Production	▪ Enteric CH_4 From Swine ▪ Enteric CH_4 From Other Animals (American Bison, Llamas, Alpacas, and Managed Wildlife) ▪ CH_4 and N_2O From Other Animals Housing[a]	▪ CH_4 From Dairy Cattle, Beef Cattle, Swine, and Poultry Housing ▪ CH_4 and N_2O From Aerobic Lagoons ▪ CH_4 and N_2O From Temporary Stack and Long-Term Stockpile ▪ CH_4 and N_2O From Composting ▪ Enteric CH_4 From Other Animals (Goats) ▪ CH_4 and N_2O From Other Animals Housing[a]	▪ Enteric CH_4 From Dairy Cattle, Sheep, Beef Cow-Calf, Bulls, Stockers, Feedlot Cattle ▪ CH_4 From Manure From Barn Floors—Dairy Cattle ▪ N_2O From Dairy Cattle, Beef Cattle, Swine, and Poultry Housing[c] ▪ CH_4 and N_2O From Anaerobic Lagoon, Runoff Holding Pond, Storage Tanks ▪ CH_4 From Anaerobic Digester	—

Source	Basic Estimation Equation	Inference	Modified IPCC or Empirical Model	Processed-Based Model
Forestry	—	—	▪ Silvicultural Practices (Reforestation; Extended Rotation; Avoided Deforestation) ▪ Fuels and Management/ Avoided Wildfire (Natural Disturbances) ▪ Urban Forest Management ▪ Harvested Wood Products	▪ Urban Forest Management ▪ Fuels and Management/ Avoided Wildfire (Natural Disturbances) ▪ Silvicultural Practices (Reforestation; Extended Rotation; Avoided Deforestation)
Wetlands	—	—	—	▪ Biomass Carbon ▪ Soil Carbon, N_2O, and CH_4
Land-Use Change	▪ Annual Change in Carbon Stocks in Dead Wood and Litter Due to Land Conversion ▪ Change in Soil Organic Carbon Stocks for Mineral Soils ▪ Annual Change in Carbon Stocks in Biomass Due to Land Conversion	—	—	—

[a] Tier used is dependent on data availability (e.g., soil and crop conditions).

Overview of Recommended GHG Estimation Methods

This report includes the most appropriate science-based approaches and specific methods for estimating farm- or forest-scale GHG emissions. For each source of GHG fluxes, table ES-2 provides a summary of the report methods, including:

- A description of the chosen methodology.
- A list of the management practices that impact GHG fluxes. For this report, management practices are defined as activities undertaken by the entity that can affect GHG emissions and removals. Examples of management practices include (but are not limited to) irrigation, tillage, and residue management for croplands.
- Emission factors used in the methodology; an emission factor is a coefficient that quantifies the emissions or removals of a gas per unit of activity.
- A brief explanation of how the methods have changed since the 2014 report. In some cases, the proposed methods have not previously been applied in specifically the way that is proposed. In other cases, the authors have proposed updated methods that reflect new science since the last report (for example, methods and data published in *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories*). While the effect of these updates on emissions cannot by quantified or generally qualified as an increase or decrease because the effect is dependent on certain activity or ancillary data (e.g., animal diet), the updates are meant to offer increased accuracy.
- A description of why the chosen methodology is an improvement over other GHG estimation methodologies.

In addition to the changes in methods listed in table ES-2, the global warming potential (GWP) values used in the calculations are updated in this report. GWP values correlate to how much heat the GHG molecules absorb in the atmosphere. Table 2-1, in chapter 2, presents the GWPs used in this report.

Table ES-2: Summary of Source Categories, Recommended Methods, and Emission Factors in This Report

Source	Methodology Approach	Management Practices	Source of Emission Factors	Update Since 2014 Methods Report	Improvements Compared to Other Greenhouse Gas Methodologies
Croplands/Grazing Lands					
Biomass Carbon Stock Changes	Herbaceous biomass and woody biomass are estimated with an empirical method using entity-specific data as input into the IPCC equations (McConkey et al., 2019; Ogle et al., 2019b). Woody biomass from trees uses allometric equations and entity-measured data (Chojnacky et al., 2014).	Changes in the estimated biomass carbon stock for cropland and grazing land if there is a land-use change or a change in the crop or forage species.	U.S.-specific default values (West et al., 2010) are used for estimating biomass carbon for annual crops and grazing lands. The IPCC default is proposed for estimating the carbon fraction value. Estimate yield (in units of dry matter) or use average values from USDA, National Agricultural Statistics Service statistics.	Updated reference to IPCC (McConkey et al., 2019; Ogle et al., 2019b)) for herbaceous biomass though the equation/methods stay the same. For woody biomass, method updates allow for a combination of Tier 1 and Tier 3.	This method was chosen because it captures the influence of land-use change and changes in crop or forage species on biomass carbon stocks by using U.S.-specific default values where entity-specific data are not available.
Soil Organic Carbon Stocks for Mineral Soils	Ogle et al. (2019a) provide the stock difference approach to estimate soil organic carbon at the beginning and end of the year for mineral soils.	Addition of carbon in manure and other organic amendments; tillage intensity; residue management (retention in field without incorporation; retention in field with incorporation; and removal with harvest, burning, or grazing); influence of bare and vegetated fallows; irrigation effects on decomposition in cropland and grazing land systems; setting aside cropland from production; influence of fire on oxidation of soil organic matter; and woody plant encroachment, agroforestry, and silvopasture effects on carbon inputs and outputs.	The DayCent model (Parton et al., 1987) or country-specific stock change factors depending on the crop and soil conditions (U.S. EPA, 2020; Ogle et al., 2019b).	Biochar amendments to soil are specifically addressed with updates provided in Ogle et al. (2019a) and described in Woolf et al. (2021).	The DayCent model has been demonstrated to represent the dynamics of soil organic carbon and estimate soil organic carbon stock change in cropland and grasslands (Parton et al., 1993). There have been uncertainties noted in the model in Ogle et al. (2007). The model captures soil moisture dynamics, plant production, and thermal controls on net primary production and decomposition with a time step of a month or less.

Source	Methodology Approach	Management Practices	Source of Emission Factors	Update Since 2014 Methods Report	Improvements Compared to Other Greenhouse Gas Methodologies
Soil Organic Carbon Stocks for Organic Soils	CO_2 emissions from drainage of organic soils (i.e., histosols) are estimated with an inference method (cf., IPCC Tier 2) using the IPCC equation (Ogle et al., 2019a).	Cropland drainage	Emission factors are from U.S. GHG Inventory (U.S. EPA 2020) and are region-specific based on typical drainage patterns and climatic controls (e.g., temperature/ precipitation) on decomposition rates.	Updated to reference IPCC (2019) though the methods remained the same (Ogle et al., 2019a).	Uses entity-specific annual data as input into the equation used in the U.S. GHG Inventory (U.S. EPA, 2020).
Direct N_2O Emissions From Mineral Soils	Use the DayCent model for major commodity crops, (e.g., corn, cotton, alfalfa). Use a modified IPCC Tier 1 (Hergoualc'h et al., 2019) with scaling factors and in cases where there are insufficient empirical data to derive a base emission rate.	Nitrogen application to crops. In addition, specific management practices are included as scaling factors. Management practices that influence a portion of the emission rate include: ▪ Use of slow-release formulation ▪ Nitrification inhibitor application Manure nitrogen directly deposited on pasture range or paddock management practices that influence the entire pool of mineral nitrogen include: ▪ Tillage ▪ Biochar amendments	For Tier 1, adjust the base emission factors with scaling factors related to specific crop management practices. Scaling factors determined from IPCC (Drösler et al., 2013; Hergoualc'h et al., 2019) or management practice scaling factors from the published literature or an analysis by the authors.	Some soil conditions updated to a Tier 1 approach.	The method is based on using results from process-based models and measured N_2O emissions in combination with scaling factors based on U.S.-specific empirical data on a seasonal timescale.
Direct N_2O Emissions From Drainage of Organic Soils	Direct N_2O emissions from drainage of organic soils, i.e., histosols, are estimated with a basic estimation equation (cf., modified IPCC Tier 1) method (Hergoualc'h et al., 2019).	Drainage of organic soils.	Emission factors are from IPCC (Drösler et al., 2013; Hergoualc'h et al., 2019) or management practice scaling factors from published literature.	Updated to reference IPCC (2019) equations but the methods remained the same (Drösler et al., 2013; Hergoualc'h et al., 2019).	Uses entity-specific annual data as input into the equation used in the U.S. GHG Inventory (U.S. EPA, 2020).

Source	Methodology Approach	Management Practices	Source of Emission Factors	Update Since 2014 Methods Report	Improvements Compared to Other Greenhouse Gas Methodologies
Indirect N_2O Emissions	Indirect soil N_2O emissions are estimated with an inference (cf., IPCC Tier 1) based on IPCC methodology (Hergoualc'h et al., 2019).	Irrigation.	IPCC defaults are used for estimating the proportion of nitrogen that is subject to leaching, runoff, and volatilization. Where cropping systems with leguminous and non-leguminous winter cover crops are grown, a U.S.-specific emission factor is provided.	Updated to reference IPCC (2019) equations but the methods remained the same (Hergoualc'h et al., 2019).	This method uses entity-specific seasonal data on nitrogen management practices.
CH_4 Flux for Nonflooded Soils	CH_4 flux by soil is estimated with an equation that uses average values for methane oxidation in natural vegetation—whether grassland, coniferous forest, or deciduous forest—attenuated by current land use practices. This approach is an empirical model (IPCC Tier 3).	Land management including cultivation for crop production, grazing in grasslands, forest harvest, grassland, or forest fertilization.	Annual average CH_4 flux emissions and removals are from a meta-analysis by the authors. Emission factors for drained organic soil from Drösler et al. (2013).	Updates address mineral and drained organic soils.	CH_4 emissions from nonflooded mineral soils are not addressed by IPCC and are not included in the U.S. GHG Inventory (U.S. EPA, 2020). The method incorporates entity-specific annual data.
CH_4 Emissions From Flooded Rice Cultivation	Either IPCC Tier 1 or 2 estimation equation, depending on the rice production region (Ogle et al., 2019b).	Scaling factors are differentiated by hydrological context (e.g., irrigated, rain fed, upland (i.e., dry soil)—all rice fields in the United States are irrigated), cultivation period flooding regime (e.g., continuous, multiple aeration), time since last flooding (prior to cultivation; e.g., more than 180 days, less than 30 days) and type of organic amendment	Linquist et al. (2018) provide emission factors specific to the California and Mid-South regions. Otherwise, default IPCC factors are available.	Updated to include IPCC Tier 2 equation for certain regions. Region-specific emission factors are built on scaling factors, amount of clay soil present, and cultivation period, among other variables.	Provides U.S.-specific considerations, including region-specific distinctions.

Source	Methodology Approach	Management Practices	Source of Emission Factors	Update Since 2014 Methods Report	Improvements Compared to Other Greenhouse Gas Methodologies
		(e.g., compost, farmyard manure).			
CO_2 From Liming	An inference (cf., IPCC Tier 2) method is used to estimate CO_2 emissions from application of carbonate limes (de Klein et al., 2006) with U.S.-specific emission factors (adapted from West and McBride, 2005).	The amount of lime, crushed limestone, or dolomite applied to soils.	U.S.-specific emission factors (West and McBride, 2005).	No change from the previous methods.	Uses U.S.-specific emission factors as annual input into the IPCC equation, which is consistent with the U.S. GHG Inventory (U.S. EPA 2020).
Non-CO_2 Emissions From Biomass Burning	Non-CO_2 GHG emissions from biomass burning of grazing land vegetation or crop residues are estimated with an inference (cf., IPCC Tier 1) method (Aalde et al., 2006).	Area burned.	Emission factors are from values in the IPCC guidelines (Aalde et al., 2006) and West et al. (2010) for the residue:yield ratios.	No change from the previous methods.	Uses entity-specific annual data as input into the IPCC equation.
CO_2 From Urea Fertilizer Application	CO_2 emissions from application of urea or urea-based fertilizers to soils are estimated with a basic estimation equation (cf., IPCC Tier 1) method (de Klein et al., 2006).	The amount of urea fertilizer applied to soils.	Emission factors are from values in the IPCC guidelines (de Klein et al., 2006). This method assumes that the source of CO_2 used to manufacture urea is fossil fuel CO_2 captured during NH_3 manufacture.	No change from the previous methods.	Uses entity-specific annual data as input into the IPCC equation.
Animal Production Systems					
Enteric Fermentation					
Dairy Cattle	Adopted from Niu et al. (2018) equation for lactating cows and Moraes et al. (2014) for	Dietary changes: increasing DMI, using fibrous concentrate rather than starch concentrate, feeding rapidly degraded starch	Emission factors needed for nonlactating and heifer populations from Moraes et al. (2014).	Updated to equations that perform best for North America, as compared to other	Niu et al. (2018) equation contained the most prediction variables and had the highest prediction

Source	Methodology Approach	Management Practices	Source of Emission Factors	Update Since 2014 Methods Report	Improvements Compared to Other Greenhouse Gas Methodologies
	both nonlactating and heifer populations. Inputs include milk fat, body weight, and dietary intake and composition.	(such as barley), and addition of dietary fat. Feeding 3-NOP, nitrates, or lipid supplementation is also included.		known sources/equations.	accuracy, similarly Moraes at al. (2014) had the highest prediction accuracy for simple models based on GEI.
Nongrazing Beef Cow-Calf, Bulls, and Stockers	IPCC (2019) Tier 2 approach. The calculation considers weight, weight gain, mature weight, pregnancy, lactation, other activity (grazing, confined, daily work), and the energy content of the animals' diets.	*Dietary changes:* considerations for additions of ionophores, supplementary fat content, changes to grain type or processing within the diet, and/or impacts of using fibrous concentrate rather than starch concentrate, feeding rapidly degraded starch (such as barley)	Emission factors are determined with the IPCC (2019) Tier 2 equation. Methane conversion factor (Y_m) based on animal-specific guidance in the U.S. GHG Inventory (U.S. EPA 2020).	Updated to reference IPCC (2019) but the equations remained the same (Gavrilova et al., 2019).	The equations utilized are the same as existing inventory methods; however, the methods use farm-specific feed types and monthly, rather than annual, data (i.e., account for seasonal variation in forage quality).
Grazing Beef Cow-Calf, Bulls, and Stockers	Modified IPCC (2019) Tier 2 approach.	*Dietary changes:* increasing DMI or methane yield dependent on feed quality. *Activity changes:* confining currently grazing animals, fewer work hours per day.	Modified IPCC (2019) equation to determine emission factor.	Updated to IPCC (2019) Tier 2 equation and default IPCC (2019) values (Gavrilova et al., 2019).	
Feedlot Cattle	IPCC (2019) Tier 2 approach. The calculation considers weight, weight gain, mature weight, pregnancy, lactation, other activity (grazing, confined, daily work), and the energy content of the animals' diets.	*Dietary changes:* increasing DMI, using fibrous concentrate rather than starch concentrate, feeding rapidly degraded starch (such as barley), and addition of dietary fat. *Activity changes:* confining currently grazing animals, fewer work hours per day, fewer days on feed prior to slaughter.	Correction factor to Y_m developed based on up-to-date research. See appendix 4-B.2.3.	Updated to reference IPCC (2019) though the equations remained the same. Updated the correction factor to Y_m.	The method provided accounts for changes in enteric CH_4 related to changes in diet or management, which Gavrilova et al. (2019) does not currently offer for default methods.

Source	Methodology Approach	Management Practices	Source of Emission Factors	Update Since 2014 Methods Report	Improvements Compared to Other Greenhouse Gas Methodologies
Sheep, When DMI Is Known	Howden et al. (1994) equation based on dietary DMI	Dietary changes, but no well-developed research due to difficulty of obtaining accurate feed-intake estimates for grazing sheep.	The equation from Howden et al. (1994) estimates emissions based solely on DMI; hence, emission factors are not utilized.	No change from the previous methods.	This method uses actual monthly estimates of DMI, rather than head count, as utilized by the IPCC (2019) Tier 1 equation.
Sheep, When DMI is Unknown	IPCC (2019) Tier 2 equation	None.	Uses IPCC (2019) default Y_m if unknown.	New method since the last version of the report. Provided to increase usability for users less familiar with diet (as compared to Howden et al. (1994) equation.)	None.
Swine	IPCC (2006) Tier 1 approach (Dong et al., 2006).	None.	Uses IPCC (2006) Tier 1 emission factor.	No change from the previous methods.	None.
Other Animals (Goats)	IPCC (2019) Tier 2 equation	None.	Uses IPCC (2019) default Y_m.	Updated to reference IPCC (2019) but the equations remained the same.	None.
Other Animals (American Bison, Llamas, Alpacas, Managed Wildlife)	IPCC Tier 1 approach for American bison (based on buffalo, modified by average animal weight), deer, llamas, and managed wildlife.	None.	Uses IPCC (2019) Tier 1 emission factors.	Updated to reference IPCC (2019) though the equations remained the same. However, Gavrilova et al. (2019) provided some updates to emission factors or other activity data.	None.
Housing					
CH_4 Emissions From Dairy Manure on Freestall Barn Floors	Empirical model by Chianese et al. (2009) For barn floors and IPCC (2019) Tier 2 for other dairy housing.	None.	Empirical relationship as provided in Chianese et al. (2009).	No updates for emissions from barn floors. Other housing updated to reference IPCC (2019), though the	Utilizes climate and entity characteristics.

Source	Methodology Approach	Management Practices	Source of Emission Factors	Update Since 2014 Methods Report	Improvements Compared to Other Greenhouse Gas Methodologies
or Other Housing				equations remained the same. However, Gavrilova et al. (2019) provided some updates to emission factors or other activity data.	
N_2O Emissions From Dairy Cattle Housing	IPCC (2019) Tier 2 approach with the amount of nitrogen excreted determined by equations from Reed et al. (2015).	Animal diets and type of manure storage.	Uses available emission factors and ammonia losses from Koelsch and Stowell (2005), Voglmeier et al. (2018); Sommer et al., (2019); Adhikari et al. (2020); Fischer et al. (2015); and IPCC (2019).	Updated to reference IPCC (2019) but the equations remained the same (Gavrilova et al., 2019). Emission factors or other activity data may have been updated, including the equations to determine nitrogen excreted.	Uses nitrogen balance approach to adjust nitrogen in housing to account for ammonia losses.
CH_4 Emissions From Beef Cattle, Swine Housing, and Poultry Housing	IPCC Tier 2 approach.	Type and duration of manure storage.	Uses a combination of IPCC (2019) and U.S. EPA (2020) Inventory emission factors.	Updated to reference IPCC (2019) though the equations remained the same (Gavrilova et al., 2019).	None.
N_2O Emissions From Beef Cattle	IPCC (2019) Tier 2 approach with the amount of nitrogen excreted determined by equations from Dong et al. (2014).	Animal diets.	For feedlot cattle use Dong et al. (2014) equation to determine nitrogen excretion.	Updated to reference IPCC (2019) but the equations remained the same. Emission factors or other activity data may have updated, including the equations to determine nitrogen excreted.	Uses nitrogen balance approach to adjust nitrogen in housing to account for ammonia losses.
N_2O Emissions From Swine,	IPCC Tier 2 approach including updated nitrogen excreted	Animal diets and type of manure storage.	Uses IPCC (2019) emission factors and ammonia losses from Koelsh and Stowell	Updated to reference IPCC (2019) though the equations remained the	Uses nitrogen balance approach to adjust nitrogen in housing to

Source	Methodology Approach	Management Practices	Source of Emission Factors	Update Since 2014 Methods Report	Improvements Compared to Other Greenhouse Gas Methodologies
		(e.g., compost, farmyard manure).			
CO_2 From Liming	An inference (cf., IPCC Tier 2) method is used to estimate CO_2 emissions from application of carbonate limes (de Klein et al., 2006) with U.S.-specific emission factors (adapted from West and McBride, 2005).	The amount of lime, crushed limestone, or dolomite applied to soils.	U.S.-specific emission factors (West and McBride, 2005).	No change from the previous methods.	Uses U.S.-specific emission factors as annual input into the IPCC equation, which is consistent with the U.S. GHG Inventory (U.S. EPA 2020).
Non-CO_2 Emissions From Biomass Burning	Non-CO_2 GHG emissions from biomass burning of grazing land vegetation or crop residues are estimated with an inference (cf., IPCC Tier 1) method (Aalde et al., 2006).	Area burned.	Emission factors are from values in the IPCC guidelines (Aalde et al., 2006) and West et al. (2010) for the residue:yield ratios.	No change from the previous methods.	Uses entity-specific annual data as input into the IPCC equation.
CO_2 From Urea Fertilizer Application	CO_2 emissions from application of urea or urea-based fertilizers to soils are estimated with a basic estimation equation (cf., IPCC Tier 1) method (de Klein et al., 2006).	The amount of urea fertilizer applied to soils.	Emission factors are from values in the IPCC guidelines (de Klein et al., 2006). This method assumes that the source of CO_2 used to manufacture urea is fossil fuel CO_2 captured during NH_3 manufacture.	No change from the previous methods.	Uses entity-specific annual data as input into the IPCC equation.
Animal Production Systems					
Enteric Fermentation					
Dairy Cattle	Adopted from Niu et al. (2018) equation for lactating cows and Moraes et al. (2014) for	Dietary changes: increasing DMI, using fibrous concentrate rather than starch concentrate, feeding rapidly degraded starch	Emission factors needed for nonlactating and heifer populations from Moraes et al. (2014).	Updated to equations that perform best for North America, as compared to other	Niu et al. (2018) equation contained the most prediction variables and had the highest prediction

Source	Methodology Approach	Management Practices	Source of Emission Factors	Update Since 2014 Methods Report	Improvements Compared to Other Greenhouse Gas Methodologies
		diets.			
N_2O Emissions	IPCC Tier 2 approach utilizing data on total initial nitrogen and dry manure.	Manure handling (i.e., no mix or active mix) and animal diets.	Uses emission factors from IPCC.	Updated to IPCC (2019) though the equations remained the same (Gavrilova et al., 2019).	Considers diet and climate characteristics.
Liquid Manure Storage and Treatment—Aerobic Lagoon					
CH_4 Emissions	The methane correction factor for aerobic treatment is negligible and was designated as 0 in accordance with the IPCC.	Not applicable.	Uses emission factors from IPCC.	No change from the previous methods.	Not estimated.
N_2O Emissions	IPCC Tier 2 method.	Configuration of storage (e.g., volume of lagoon), natural or forced aeration, and animal diets.	Uses emission factors from IPCC.	Updated to IPCC (2019) but the equations remained the same (Gavrilova et al., 2019).	None.
Liquid Manure Storage and Treatments—Anaerobic Lagoon, Runoff Holding Pond, Storage Tanks					
CH_4 Emissions	IPCC (2019) Tier 2 method.	Configuration of storage unit (e.g., covered or uncovered storage, presence or absence of crust) and animal diets.	Uses "MCF Calculations Example Spreadsheet" from IPCC (2019).	Updated from the Sommer et al. (2004) model.	Considers diet and storage temperature characteristics.
N_2O Emissions	Emissions are a function of the exposed surface area and U.S.-specific emission factors.	Configuration of storage unit (e.g., surface area of manure).	Uses emission factors from Rotz et al. (2011).	No change from the previous methods.	Utilizes U.S.-specific emission factors.
Liquid Manure Storage and Treatment—Anaerobic Digestion With Biogas Utilization					
CH_4 Emissions	Leakage from anaerobic digestion system is estimated using IPCC Tier 2 approach and system- specific emission factors.	Configuration of digester (e.g., steel or lined concrete or fiberglass digesters) and animal diets.	Utilizes emission factors from CDM (CDM, 2012).	Updated to reference IPCC (2019) but the equations remained the same (Gavrilova et al., 2019).	Considers system design and diets.
N_2O	Not estimated due to	Not applicable.	Not applicable.	No change from the	Not applicable.

Source	Methodology Approach	Management Practices	Source of Emission Factors	Update Since 2014 Methods Report	Improvements Compared to Other Greenhouse Gas Methodologies
Emissions	negligible GHG emissions.			previous methods.	
Forestry					
Silviculture Practices and Improved Forest Management	Methods include: (1) Excel workbook-facilitated emissions estimates, with or without changing practices overtime; (2) user-specified or site-specific removal or emission factors; or (3) using forest vegetation simulator (FVS) modeling with Forest Inventory Analysis (FIA) data.	Type of management (forest maintenance, reforestation, extending rotation, or avoiding deforestation), and years before harvest.	FIADB (Burrill et al., 2021) data used in creating lookup tables for nonuser specified data.	Creation of an accompanying Excel workbook to simplify calculations for users. Basis of allometric equations updated from only Jenkins et al. (2003) to considerations from Chojnacky et al. (2014) and Woodall et al. (2011).	Gain-loss approach used aligns with other GHG inventories.
Harvested Wood Products	Method is an Excel workbook facilitated carbon stocks and emissions estimation for products in use and in landfills, as well as potential substitution benefits.	Type of management (avoided deforestation, extended rotation, harvest), and harvest volume.	Various regional factors from Smith et al. (2006).	Creation of an accompanying Excel workbook to simplify calculations for users. Updated from referencing the WOODCARB II model to improve calculations with other known data sources [Smith et al. (2006), Skog (2008), McKeever (2009) and McKeever and Howard (2011)].	Builds on WOODCARB II to adhere to the IPCC production approach. Aims to provide a novel cradle to grave approach.
Urban Forests	Methods include: (1) Field Data Method using i-Tree Eco, i-Tree MyTree, i-Tree Design;	Maintenance (use of vehicles, chain saws, etc.) and altering building energy use (use of trees for shading and wind	i-Tree Eco model; i-Tree Canopy model.	Additional i-Tree tools were identified for use and varying levels of user technical ability as	This method provides a range of options dependent on the data availability of the entities'

Source	Methodology Approach	Management Practices	Source of Emission Factors	Update Since 2014 Methods Report	Improvements Compared to Other Greenhouse Gas Methodologies
	(2) Aerial Method using i-Tree Canopy model with aerial tree cover estimates and look up tables; and (3) Online Geospatial Database Method using i-Tree Landscape.	breaks); quantitative methods for estimating emissions from these management practices are included for information purposes only.		well as data access.	urban forest land.
Wildfire and Prescribed Fire	Methods include: (1) Excel workbook-facilitated emissions estimates for certain fire scenarios (2) Inventory data combined with model simulations- e.g., First Order Fire Effects Model (FOFEM) or FVS with the Fire and Fuels Extension (FFE).	Fire and fuel load management.	Simulations using FIADB data as input to the FFE-FVS.	Creation of an accompanying Excel workbook to simplify calculations for users.	This method provides a range of options dependent on the data availability of the entities' disturbed forest land.
Wetlands					
Biomass Carbon in Wetlands	Methods for estimating forest vegetation and shrub and grassland vegetation biomass carbon stocks use a combination of the FVS model and lookup tables for dominant shrub and grassland vegetation types found in the Cropland and Grazing Land Chapter (chapter 3). If there is a land-use change, methods for cropland herbaceous biomass are suggested.	Forested Wetlands: Same as those generally described in chapter 5. Shrub and Grassland Vegetation: Same as those described for total biomass carbon stock changes presented in chapter 3.	Forest Wetlands: Regional variants are available for FVS that allow for region-specific focus on species and forest vegetation communities. The driver for productivity is the availability of site index curves, and the regional variants include many wetland tree species. However, if a species-specific curve is not available, then a default function is used to estimate carbon stock changes. Shrub and Grassland	No revisions in this report update.	Uses entity-specific seasonal data. No IPCC methodologies currently exist for this source; hence, this is a newly developed method.

Source	Methodology Approach	Management Practices	Source of Emission Factors	Update Since 2014 Methods Report	Improvements Compared to Other Greenhouse Gas Methodologies
			Vegetation: Same as chapter 3.		
Soil Carbon, N_2O, and CH_4 in Wetlands	The DeNitrification-DeComposition (DNDC) process-based biogeochemical model is the method used for estimating soil carbon, N_2O, and CH_4 emissions from wetlands.	Vegetation management, water management regime, soil management, fertilization practices, and land-use history.	Process based model is used; hence, no emission factors are used in this method.	No change from the previous methods.	This method leverages the DNDC model to simulate soil carbon, N_2O, and CH_4 emissions from wetlands on a seasonal timescale.
Land-use Change					
Annual Change in Carbon Stocks in Dead Wood and Litter Due to Land Conversion	A basic estimation equation (cf., IPCC Tier 1) is used to estimate change in carbon stocks in dead wood and litter (Aalde et al., 2006).	Land conversion.	IPCC 2006 Guidelines (Aalde et al., 2006).	No change from the previous methods.	Uses entity-specific annual data as input into the equation and is consistent with IPCC 2006 guidance.
Change in Soil Organic Carbon Stocks for Mineral Soils	The methodologies to estimate soil carbon stock changes for organic soils and mineral soils are adopted from IPCC (Ogle et al., 2019a) and are a basic estimation equation.	Land conversion.	IPCC 2019 Refinements (Ogle et al., 2019a).	Updated to IPCC (2019) though the equations remained the same (Ogle et al., 2019a).	Uses entity-specific annual data as input into the equation and is consistent with IPCC 2019 refinements.
Annual Change in Biomass Carbon Stocks Due to Land Conversion	A basic estimation equation is used to estimate the change in carbon stocks in biomass due to land conversion (Aalde et al., 2006).	Land conversion.	IPCC 2006 Guidelines (Aalde et al., 2006)	New method since the last version of the report.	None.

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Chapter 1
Introduction

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Acronyms, Chemical Formulae, and Units

C	carbon
CH_4	methane
CO_2	carbon dioxide
CO_2-eq	carbon dioxide equivalents
GHG	greenhouse gas
LCA	life cycle assessment
N_2O	nitrous oxide
NMVOC	non-methane volatile organic compounds
USDA	U.S. Department of Agriculture
U.S. EPA	U.S. Environmental Protection Agency

1. Introduction

This report provides a scientific basis and methods for estimating greenhouse gas emissions (GHGs) and sinks from management practices at an entity level (see box 1-1) for a farm, ranch, or forest system. The methods have been developed for U.S. conditions and are considered applicable to agricultural and forestry production systems in the United States. The report covers the following land-use sectors: croplands/grazing lands, managed wetlands, animal production systems, and forestry, along with changes in land use. The report does not provide methods for lands categorized as settlements (e.g., residential and commercial buildings).

Box 1-1. Definition of Entity

An **entity** is defined as all activities occurring on all tracts of land under the ownership and/or management control—now and for the foreseeable future—of a farm, ranch, or forest landowner or manager.

1.1 Overview of GHG Emissions, Sinks, and Fluxes in Agriculture and Forestry

Since the onset of the Industrial Revolution, global atmospheric concentrations of greenhouse gases (GHGs)—including carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O)—have measurably increased. GHGs trap heat in the atmosphere, making the planet warmer. Since 1880, the average global temperature has increased at least 1.1 °C (NASA Earth Observatory, 2022).

Agriculture and forestry practices are both a source and sink of GHGs. Agricultural soils, enteric fermentation from ruminant livestock production, managed livestock manure, wetlands, rice cultivation, and agricultural residue burning all produce GHG emissions. Activities that capture and sequester carbon in biomass, wood products, and soils and remove CO_2 from the atmosphere are called sinks. Mitigation practices can reduce GHG emissions and increase sinks. GHG fluxes are the exchange of GHGs between the atmosphere and the earth via emissions, deposition, or absorption.

Agricultural activities contributed 11 percent of the net total GHG emissions in the United States in 2020 (U.S. EPA, 2022). These activities include N_2O emissions from agricultural soil management, livestock manure management, and field burning of agricultural residues; CH_4 emissions from enteric fermentation, livestock manure management, rice cultivation, and field burning of agricultural residues; and CO_2 emissions from liming and urea fertilization. Of these activities, agricultural soil management, enteric fermentation, and manure management accounted for approximately 90 percent of U.S agriculture sector emissions in 2020 (see figure 1-1). Emissions and sinks associated with cropland cultivation, grassland management, grassland fires, and the conversion of other land uses into cropland are included in the land use, land-use change, and forestry (LULUCF) sector. The LULUCF sector sequestered enough carbon in 2020 to offset about 13 percent of total U.S. GHG emissions (U.S. EPA, 2022).

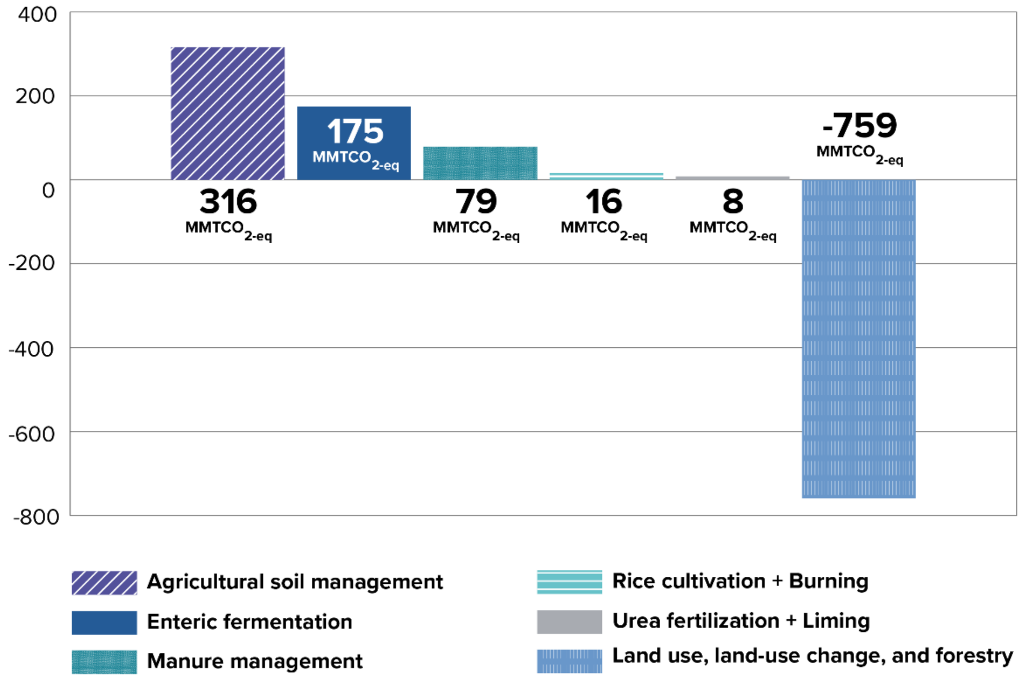

Figure 1-1. Agricultural Net GHG Emissions and Sinks in 2020

Figure 1-2 depicts GHG fluxes from agriculture and forestry systems included in this report. This includes fluxes from croplands and grazing lands (biomass, litter and soil stock changes, rice cultivation, non-flooded soils, urea and liming, biomass burning), animal production (enteric fermentation, manure, and housing), forestry (silviculture, harvested wood products, forest fires, biomass burning, litter/deadwood, litter clearing, urban forest management), and wetlands.

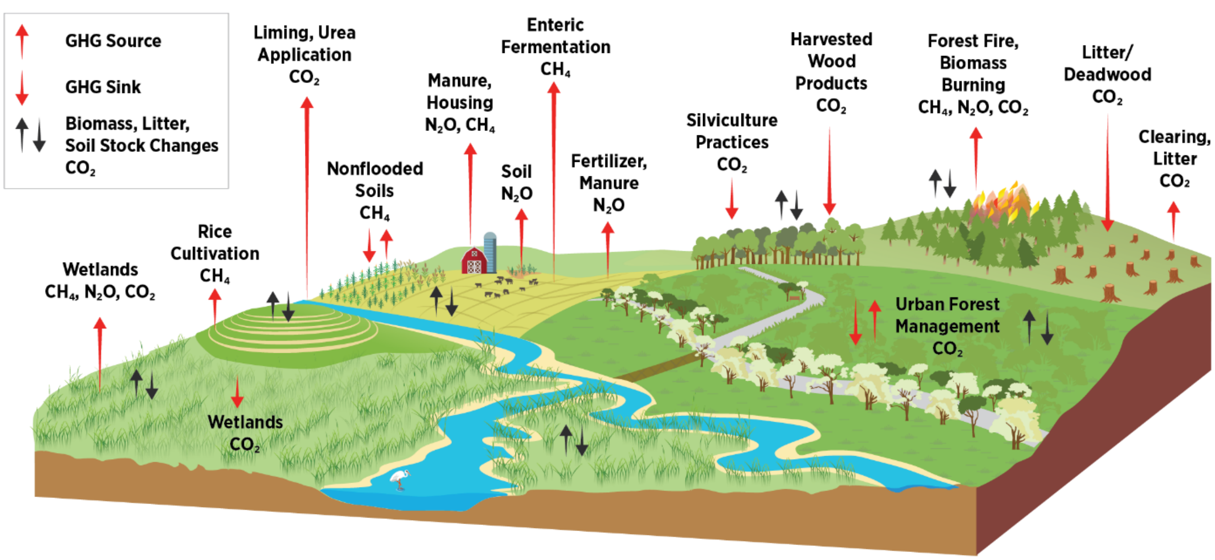

Figure 1-2. The Main GHG Emission Sources and Sinks in Agriculture and Forestry Systems

1.1.1 Report Development Process

In 2008, Section 2709 of the Food, Conservation, and Energy Act directed USDA to "establish technical guidelines that outline science-based methods to measure the environmental service benefits from conservation and land management activities in order to facilitate the participation of farmers, ranchers, and forest landowners in emerging environmental services markets." In response to this legislation, USDA released the first version of this report in 2014, *Quantifying Greenhouse Gas Fluxes in Agriculture and Forestry: Methods for Entity-Scale Inventory*.

In 2019, three author teams consisting of 10 to 50 working group members began an update of the 2014 report. All working group members had experience with GHG accounting and/or field research that addressed one or more of the methods needed. Each author team received relevant content from the 2014 report, an outline for the updated report, and a background report (Ogle et al., 2020) summarizing the scientific literature related to the GHG mitigation potential, cost, and feasibility of different management practices.

The review process for this report consisted of:

- **USDA technical review.** USDA's intra-agency review raised a series of comments and questions for the chapter authors. The chapter authors addressed these comments without additional formal meetings.
- **Concurrent interagency and scientific expert technical review.** Once the intra-agency review draft was complete, an interagency group of GHG emissions and inventory experts reviewed the revised draft. The reviewers included individuals from academia, USDA, the U.S. Department of Energy, the U.S. Department of the Interior, the U.S. Environmental Protection Agency (EPA), the U.S. Department of State, and several White House offices. These reviewers were chosen for their recognized expertise, experience in expert reviews, and willingness to participate. This review produced a series of comments and questions for the authors to address.
- **Concurrent Highly Influential Scientific Assessment peer review and public comment period.** Once all the expert comments were addressed, the report was made available for public comment. This review coincided with a final review by USDA and other Federal agency GHG experts. Chapter authors assessed and addressed these comments, and the report was edited for publication.

1.1.2 Changes From the 2014 Report

This report includes updates to the estimation methods to reflect the current state of the science as well as to increase transparency and user friendliness. General rearranging of the chapters occurred, which changed the numbering for several chapters from the 2014 report. Most updates occurred in *Chapter 3: Cropland and Grazing Land Systems*, *Chapter 4: Animal Production Systems*, and *Chapter 5: Managed Forest Systems*. Within these chapters, methods were updated to reflect the most recent science, and efforts were made to streamline the text to make the methods more prominent.

1.1.3 Report Purposes

This report has several important purposes, including the following:

- Enabling landowners and others to accurately estimate GHG fluxes and impacts at an entity scale, including fluxes associated with different management practices.

- Providing methods to help USDA accurately estimate GHG fluxes from current and future conservation programs and practices and assessing the performance of conservation and renewable energy programs. Note that the intensity metrics of GHGs (i.e., emissions per production unit) are not explicitly addressed in this guidance.
- Providing a basis for updating USDA's GHG flux estimation tools, including COMET-Planner and COMET-Farm (see box 1-2).
- Informing GHG estimates for other programs. For example, this report may inform emerging methods that underly voluntary GHG registries, facilitate regional GHG markets, and provide technical inputs for future GHG reporting programs.

Box 1-2. COMET-Planner and COMET-Farm Tools

- COMET-Planner provides generalized estimates of GHG impacts of conservation practices.
- COMET-Farm is a publicly available, user-friendly web-based tool that estimates detailed, farm-specific GHG fluxes. The tool can help users evaluate different options for reducing GHG emissions and sequestering carbon.

Figure 1-3 illustrates how these methods inform practice, technology research, and methods development at national, program, and farm levels. Entity-scale estimates may be scaled up to the program and national level, and have impacts on U.S. Government strategy and the *Inventory of U.S. Greenhouse Gas Emissions and Sinks.*

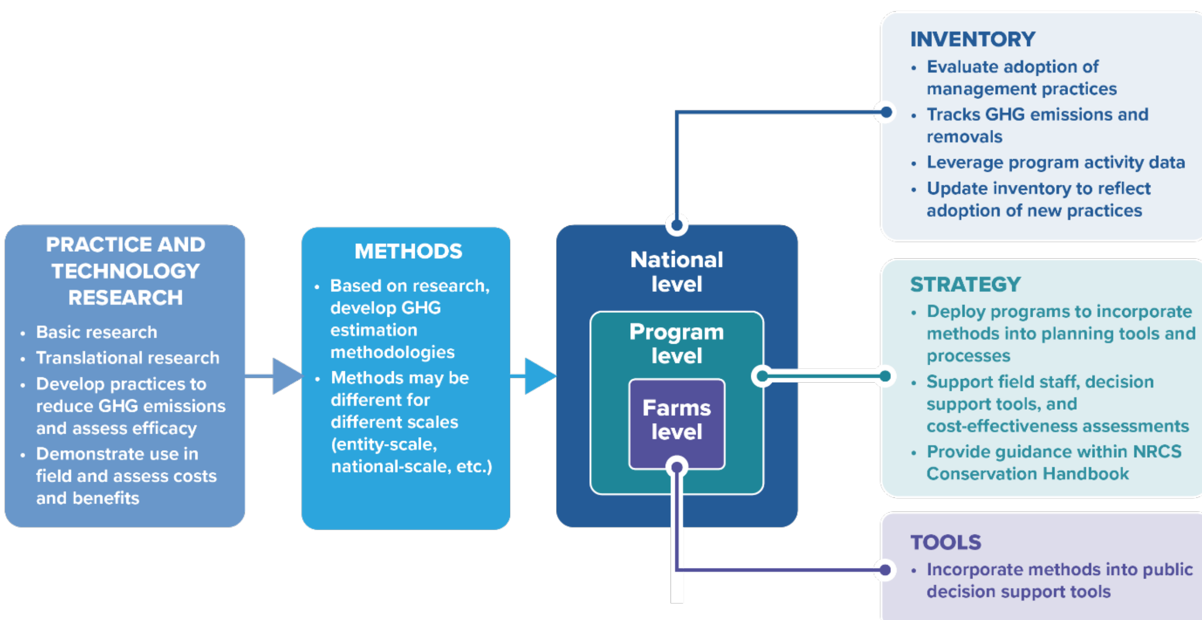

Figure 1-3. Agricultural GHG Estimation Research, Methods, and Applications

In addition, the methods are designed to:

- **Be independent, yet consistent and transparent**. The methods are designed to stand on their own, independent of any other accounting system, yet stay as consistent as possible with other accounting systems. For example, the methods are consistent with the *Inventory of U.S. Greenhouse Gas Emissions and Sinks* where appropriate so that entity-scale data can be compared with the national inventory.
- **Provide flexibility.** The methods are designed to estimate fluxes for the entirety of a farm, ranch, or forest, but are also appropriate for evaluating a single management practice implemented within a single farm, ranch, or forest or aggregated across multiple farms, ranches, or forests. They can also be adapted to county or State levels. The methods are also intended to maintain maximum applicability for potential use in environmental markets.
- **Address practical concerns around GHG estimation.** This includes the risk of reversal if management practices revert in the foreseeable future. (For example, a land manager must understand that a change in management that results in soil carbon sequestration, if reversed, will likely lead to the extra stored carbon being released to the atmosphere.)
- **Display consistency and transparency in reporting.** The methods were intended to facilitate entity-level reporting by a diversity of users with a wide range of technical capacities and data availability.
- **Calculate GHG fluxes over time.** The methods can be used to estimate emissions, sinks, and removals across multiple years, showing changes over time.
- **Allow for integrated estimates.** This report brings estimation approaches from all agriculture and forestry sectors into one report so that an integrated estimate can be derived for all activities within the boundary of a farm, ranch, or forest operation**.**

1.1.4 Appropriate Uses and Limitations of the Report

When using or referencing this report, the following considerations should be kept in mind:

- The report generally does not provide a range of emission/sequestration accounting options at varying levels of complexity (i.e., tiers) for each source category. However, chapter 5 specifies individual options for entities within source categories where there are significant differences in data and/or user familiarity.
- **The methods are not intended to provide a life cycle assessment (LCA).** LCAs evaluate the entire lifespan of a commodity or product to fully quantify its environmental impact. This report focuses on emissions that occur at the entity-scale annually. It does not provide the methods required to quantify upstream production (e.g., animal feed production, fertilizer manufacture) or downstream production (e.g., wastewater treatment, pulp and paper manufacture, or landfills), except for harvested wood product treatment, which is discussed in chapter 5.
- The methods are not meant for estimating emissions from stationary source combustion (e.g., burning heating oil or natural gas to heat animal housing) or mobile source combustion (e.g., fuel use in vehicles), with the exception of chapter 5, which includes emission reductions that occur when substituting woody biomass for nonrenewable energy sources. However, the report does qualitatively discuss obvious changes in combustion levels due to a management practice change. For example, a shift from conventional tillage to no-till can significantly reduce fuel consumption since fewer trips across the field are needed. Methods for quantifying emissions from stationary or mobile combustion sources

are available from other Federal agencies (e.g., EPA's *Inventory of U.S. Greenhouse Gas Emissions and Sinks*), and a calculator that provides emissions reductions associated with changes in on-farm fuel or electricity use is available at the COMET-Energy website.

1.1.5 Report Contents

The report is intended to be considered in its entirety, with the chapters 1 and 2 providing context for the sector content in chapters 3 through 7 (see box 1-3 for a description of how these chapters are structured). Chapter 8 provides a framework for estimating uncertainty, and the appendixes provide additional technical background, methods documentation, and a discussion of research gaps and other estimation methods.

Box 1-3. Organization of Sector Chapters

Each sector chapter provides:

- Brief background and information on management practices.
- The methods that demonstrate the current best approach to estimating GHG fluxes, balancing the available science and data with the criteria and considerations mentioned previously.
- Discussion of research gaps or priority areas for future data collection that are important to improve the completeness or accuracy of the estimation methods.
- Information about uncertainty and limitations of the methods.

The report is organized as follows:

- **Chapter 1: Introduction.** Describes the objectives of the report, the methods and report development process, and the limitations of the methods presented. Also provides an overview of the sectors covered in the report, and the management practices that influence GHG estimations.
- **Chapter 2: Considerations When Estimating Greenhouse Gas Fluxes from Agriculture and Forestry.** Sets the context for the methods, including linkages and cross-cutting issues that span the sectors, including the definitions of system boundaries. Includes a brief discussion of GHG remote sensing and emissions technologies.
- **Chapter 3: Quantifying Greenhouse Gas Sources and Sinks in Cropland and Grazing Land Systems.** Presents methods for estimating the influence of land use and management practices on GHG emissions (and sinks) in crop and grazing land systems. Methods are described for estimating biomass and soil carbon stocks changes, direct and indirect soil N_2O emissions, methane (CH_4) and N_2O emissions from wetland rice, CH_4 uptake in soils, carbon dioxide (CO_2) emissions or sinks from liming, non-CO_2 GHG emissions from biomass burning, and CO_2 emissions from urea fertilizer application.
- **Chapter 4: Quantifying Greenhouse Gas Sources and Sinks in Animal Production Systems.** Presents enteric fermentation, manure management, and housing methods appropriate for each common livestock sector (i.e., beef, dairy, sheep, swine, and poultry).
- **Chapter 5: Quantifying Greenhouse Gas Sources and Sinks in Managed Forest Systems.** Provides guidance on estimating carbon sequestration and GHG emissions for the forestry sector. Presents an overview of forest carbon accounting elements, including key carbon pool definitions and methods for their estimation. "Levels" are provided for this chapter to allow flexibility for users with ranges of knowledge, available data, and resources.
- **Chapter 6: Quantifying Greenhouse Gas Sources and Sinks in Managed Wetland**
– **Systems.** Provides guidance on estimating carbon stock changes, CH_4, and N_2O emissions from actively managed wetlands.

- **Chapter 7: Quantifying Greenhouse Gas Sources and Sinks From Land-Use Change.** Provides guidance on estimating the net GHG flux resulting from changes between land types—i.e., conversions into and out of cropland, wetland, grazing land, or forestland—at the entity scale.
- **Chapter 8: Uncertainty Assessment for Quantifying Greenhouse Gas Sources and Sinks.** Provides a framework for a Monte Carlo assessment of estimation uncertainty.
- **Chapter Appendixes:** Include background technical information, including descriptions of systems, biological processes, general interactions, or emissions generation (or sinks) processes. Provide method documentation, including the rationale for the method, sometimes describing why a method was preferred over another available method, in addition to supplemental technical documentation of chosen methods. Describes current research gaps the authors are aware of and sometimes where there are potential other methods or processes.

1.2 Overview of Sectors, Management Practices, and Estimation Methods

This section provides a brief description of each sector covered in this report, along with their key emissions and sinks. The management practices that affect GHG emissions for each sector are also listed, as well as the chapter to use when estimating GHGs for the sector.

Box 1-4. Definition of Management Practice

For this report, ***management practices*** are defined as activities an entity undertakes that can affect GHG emissions and removals. Examples of management practices include (but are not limited to) irrigation, tillage, and residue management for croplands.

When estimating GHG emissions using the methods in this report, it is important for landowners to provide a complete description of the management practices (see box 1-4) used. This is because the influence of management practices on GHG emissions is not typically the simple sum of each practice's effect. Instead, one practice can influence another. Different variables, such as soil characteristics and weather or climate conditions, also have an impact. For example, the influence of tillage on soil carbon depends on residue management. The influence of nitrogen fertilization rates can depend on fertilizer placement and timing. Note also that trends in GHG emissions associated with a change in management practices can be reversed if the landowner reverts to the original practice.

1.2.1 Croplands and Grazing Lands

Croplands include all systems used to produce food, feed, and fiber commodities, as well as feedstocks for bioenergy production. Most U.S. croplands are drylands (nonwetlands, irrigated or unirrigated); rice and a few other crops are grown in wetlands. Croplands also include agroforestry systems that are a mixture of crops and trees, such as alley cropping, shelterbelts, and riparian woodlots.

Grazing lands are systems used for livestock production and occur primarily on grasslands. Grasslands are composed principally of grasses, grass-like plants, forbs, or shrubs suitable for grazing and browsing; they include both pastures and native rangelands (U.S. EPA, 2022). Other lands (i.e., savannas, some wetlands, tundra) can be considered grazing lands if used for livestock production. Grazing lands include native rangelands as well as pastures that may need periodic management to maintain grass.

Cropland and grazing lands are significant sources of CO_2, N_2O, and CH_4 emissions and can also be a sink for CO_2 (U.S. EPA, 2022). Climate and soil characteristics can impact all GHG fluxes. Land use and management activities, particularly nitrogen application, influence N_2O emissions from soils. Fertilizer rate, timing, and placement, along with nitrogen source, are the main influences on nitrogen use efficiency and N_2O emissions. Land use and management also influence carbon stocks in biomass, dead biomass, and soil pools. Tillage intensity, cropping intensity, and crop rotation can significantly affect soil carbon stocks. Box 1-5 presents other management activities that affect GHG emissions and sinks from croplands and grazing lands.

Box 1-5. Management Practices Affecting GHG Emissions From Croplands and Grazing Lands

- Nutrient management (synthetic and organic)
- Tillage practices
- Crop rotations, cover crops, and cropping intensity
- Water management (i.e., irrigation, drainage)
- Erosion control
- Management of drained wetlands
- Lime amendments
- Residue management
- Set-aside/reserve cropland
- Biochar amendments to soils
- Flooded rice cultivation
- Livestock grazing practices
- Forage options
- Management to address woody plant encroachment
- Windbreaks
- Alley cropping
- Riparian forest buffers

Which Estimation Methods To Use?

Follow the methods in **Chapter 3: Croplands and Grazing Land** if any of the following apply:

- You manage cropland. Delineate the management units where crop production is the primary activity.
- You manage grazing land. Delineate units where grazing is the primary activity.
- You manage orchards, vineyards, or other agroforestry lands. Delineate management units by crop and management practice.

1.2.2 Animal Production

GHG emissions from animal production systems fall into three main categories: enteric fermentation, housing, and manure management.

Enteric fermentation takes place in animal digestive systems, particularly in ruminant animals. CH_4 is formed in the rumen (the first stomach compartment) as microbial fermentation breaks down food. CH_4 can also arise from hindgut fermentation, but at much lower levels. Several diet management practices can modify enteric fermentation estimates (see box 1-6).

Box 1-6. Management Practices Affecting GHG Emissions From Enteric Fermentation

- Composition of the diet
- Level of dry matter intake
- Feed additives

CH_4 is the only GHG of concern in enteric fermentation. Field studies have confirmed that enteric fermentation does not produce N_2O or ammonia (NH_3) (Reynolds et al., 2010). Although animals produce CO_2 through respiration, the annual net CO_2 is assumed to be zero due to plant photosynthesis (IPCC, 2006).

Housing emissions refer to GHG emissions from manure stored within the housing structure (e.g.., under a barn floor). GHG emissions from manure stored in housing are similar to emissions from manure managed in stockpiles. The main solid manure storage and treatment practices are temporary stacks, long-term stockpiles, and composting. The main liquid manure storage and treatment practices are aerobic lagoons, anaerobic lagoons, runoff holding ponds, storage tanks, anaerobic digestion with biogas utilization, and solid-liquid separation.

The treatment and storage of manure in management systems contributes to CH_4 and N_2O emissions. The magnitude of CH_4 and N_2O emissions from animal manure depends largely on environmental conditions. CH_4 is emitted in anaerobic conditions when oxygen is not available for bacteria to decompose manure, such as when manure is stored in ponds, tanks, or pits, as is typical with liquid/slurry flushing systems. Storing solid manure in stacks or dry lots or depositing it on pasture, range, or paddocks tends to result in more aerobic conditions, in which little or no CH_4 will be formed. Other factors that influence CH_4 generation include the ambient temperature, moisture content, residency time, and manure composition (which depends on the diet of the livestock, growth rate, and type of digestive system) (U.S. EPA, 2022).

Similarly, direct N_2O emissions from livestock manure depend on the manure composition (manure includes both feces and urine), the type of bacteria involved in the process, and the amount of oxygen and liquid in the manure system (U.S. EPA, 2022). N_2O forms when the manure is first subjected to aerobic conditions where NH_3 and organic nitrogen are converted to nitrites and nitrates (nitrification). If conditions become sufficiently anaerobic, the nitrates and nitrites can be denitrified (reduced to nitrogen oxides and nitrogen gas) (Robertson and Groffman, 2015). N_2O is an intermediate product of both nitrification and denitrification and can be directly emitted from manure as a result of either of these processes. Dry waste handling systems are generally oxygenated but have pockets of anaerobic conditions from decomposition—conditions that are most conducive to the production of N_2O (USDA, 2022).

Some manure management systems can effectively mitigate the release of GHG emissions from livestock manure. Box 1-7 lists several practices that can influence manure management emissions.

Box 1-7. Management Practices Affecting GHG Emissions From Manure Management

- Type of manure storage
  - Liquid or dry
  - Covered or uncovered
  - Aerated
  - Amendments or additives
- Conditions of manure storage
  - Storage time
  - Climate
- Anaerobic digestion

Which Estimation Methods to Use?

Follow the methods in **Chapter 4: Animal Production Systems** if any of the following apply:

- You manage beef cattle (cow-calf, stocker, and feedlot systems), dairy cattle, sheep, swine, or poultry (layers, broilers, and turkeys).
- You collect manure.

Follow the methods in Chapter 3: Cropland and Grazing Land if:

- You apply manure to land.

1.2.3 Forestry

Forest systems represent a significant opportunity to mitigate GHGs through the sequestration and temporary storage of forest carbon stocks. Forests remove CO_2 from the atmosphere through photosynthesis and store carbon in forest biomass (e.g., stems, root, bark, leaves) and soil, and release CO_2 to the atmosphere via the microbial decomposition of biomass (otherwise termed respiration) and/or combustion of biomass. Net forest carbon stocks increase over time when carbon sequestration during photosynthesis exceeds carbon released during respiration and combustion. Other GHGs are also exchanged by forest ecosystems, such as CH_4 from microbial communities in forest soil and N_2O from fertilizer use, nitrogen deposition, and soil organic matter decomposition.

Harvesting forests releases some sequestered carbon to the atmosphere, while harvested wood products (HWPs) contain the remaining carbon. How HWPs are used (e.g., combustion for energy, manufacture of durable wood products, disposal in landfills) determines the rate at which the carbon is returned to the atmosphere.

Many management practices can reduce GHG emissions and/or increase carbon stocks in the forestry sector, including establishing and/or re-establishing forest, maintaining forest stands, and avoiding forest clearing (see box 1-8).

Box 1-8. Management Practices Affecting Net GHG Emissions From Forestry

- Establishing and reestablishing forest
- Maintaining forest stands
- Stand density management
- Site preparation techniques
- Vegetation control
- Planting
- Natural regeneration
- Fertilization
- Selection of rotation length
- Harvesting and utilization techniques
- Fire and fuel load management
- Reducing the risk of emissions from natural disturbances
- Short-rotation woody crops

Which Estimation Methods To Use?

Follow the methods in **Chapter 5: Forestry** if any of the following apply:

- You manage lands for timber production for lumber, pulp, biofuels or other products. Delineate timber management units.
- **You manage trees outside forests or agroforestry.** Delineate management units that consist of trees outside forests

1.2.4 Wetlands

Wetlands are areas that are either periodically or permanently wet or saturated. Wetlands occur across the United States on many landforms, particularly in floodplains and riparian zones, inland lacustrine systems, glaciated outwash, and coastal plains. The National Wetlands Inventory broadly classifies wetlands into five major systems (Cowardin et al., 1979; DESQ, 2015):

- **Marine:** Includes the ocean or estuary coastline to a given jurisdictional limit.
- **Estuarine:** Tidal wetlands with access to freshwater dilution.
- **Riverine:** Wetlands within a channel of water that connects two enclosed bodies of water.
- **Lacustrine:** Open, nonvegetated systems of a large size (>8 hectares).
- **Palustrine:** Small-sized (<8 hectares) nontidal wetlands with emergent vegetation.

These systems are further classified by major vegetative life form. For example, forested wetlands are often classified as palustrine-forested. Similarly, most grassland wetlands are classified as palustrine wetlands with emergent vegetation (e.g., grasses and sedges). Wetlands also vary greatly with respect to groundwater and surface water interactions that directly influence hydroperiod, water chemistry, and soils (Cowardin et al., 1979; Winter et al., 1998). All these factors, along with climate and land-use drivers, influence overall carbon balance and GHG flux.

The degree of water saturation, as well as climate and nutrient availability, largely control GHG emissions from wetlands. CH_4 is the primary emission from wetlands, which is produced by anaerobic soils that characterize wetland systems. In aerobic conditions (which may occur seasonally in upland wetland ecosystems), decomposition releases CO_2; in anaerobic conditions, it releases CH_4. N_2O emissions from wetlands are typically low unless an outside source of nitrogen is entering the wetland.

Management of the water table within a wetland results in lower CH_4 emissions and an increase in CO_2 emissions due to oxidation of soil organic matter and an increase in N_2O emissions in nutrient-rich soil, while the creation or restoration of wetlands reduces soil N_2O and CO_2 emissions, but increases soil CH_4 emissions (IPCC, 2006).

This report mainly focuses on restoration and management practices associated with riverine and palustrine systems in forested, grassland, and riparian ecosystems. Although other major wetland systems (e.g., estuarine) are significant in the global carbon cycle, these systems have received the most attention in terms of implementation of restoration and management practices to conserve wetlands habitats and sustain ecosystems services (Brinson and Eckles, 2011). Wetlands that have been drained for production of a commodity such as annual crops are not considered wetlands in this report.

Grassland and forested wetlands are subject to a wide range of land use and management practices that influence the carbon balance and GHG flux (Faulkner et al., 2011; Gleason et al., 2011). For example, forested wetlands may be subject to silvicultural prescriptions, and grassland wetlands may be grazed, hayed, or directly cultivated. All these manipulations influence the overall GHG flux. Biomass carbon can change significantly with wetland management, particularly in peatlands and forested wetlands, or when wetlands change from forest to lands dominated by grasses and shrubs or open water. Box 1-9 lists the management practices in wetlands that have an influence on GHG emissions or carbon stock changes.

Box 1-9. Management Practices Affecting GHG Fluxes From Wetlands

- Silvicultural water table management
- Forest harvesting systems
- Forest regeneration systems
- Fertilization
- Conversion to open wetland
- Forest type change
- Water quality management
- Wetland management for waterfowl
- Constructed wetlands for wastewater treatment
- Land-use change to wetlands
- Actively restoring wetlands
- Actively restoring scrub-grass wetlands
- Constructing wetlands
- Passive restoration of wetlands

Which Estimation Methods To Use?

Follow the methods in **Chapter 6: Wetlands** if:

- You manage naturally occurring wetlands or restored wetlands on previously converted wetland sites and do *not* cultivate rice. Delineate management units of naturally occurring or restored wetlands.

Follow the methods in **Chapter 3: Croplands and Grazing Land** if:

- You cultivate rice.
- You manage wetlands drained for commodity production.

1.3 Land-Use Change

Converting land parcels from one land-use category to another can significantly affect a parcel's carbon stocks. For example, converting cropland to wetlands or forestland can cause carbon stock gains, while converting forestlands to grazing lands often causes carbon stock losses. In addition, land-use changes can affect soil organic carbon, particularly when land is converted to croplands (Six et al., 2000).

In many cases, the methods for estimating contributions to the GHG flux resulting from land-use change are the same as those used to estimate carbon stock changes in the other sector chapters; in certain cases, it is also necessary to reconcile carbon-stock estimates between discrete datasets and estimation methods (e.g., reconciling forest soil carbon estimates and cropland soil carbon estimates for land-use change from forestland to cropland).

The methods for quantifying GHG flux from land-use change are intended for use on lands managed to enhance the production of food, feed, fiber, and renewable energy. Methods are currently not provided for estimating emissions from energy used when converting land use from one category to another. Nor are methods provided for land-use change from settlements or the "other land" category to cropland, grazing land, wetland, or forestland.

Which Estimation Methods To Use?

Follow the methods in **Chapter 7: Land-Use Change** if you have changed land use in the past year and the land use changed from one to another of the following categories:

- Forest land
- Cropland
- Grazing land
- Wetlands

1.4 General Description of Available Tools and Methods

A landowner or manager can use several approaches to estimate GHG emissions at an entity scale. Each one gives varying accuracy and precision. The most accurate way to estimate emissions is direct measurement, which often requires expensive equipment or techniques that are not feasible for a single landowner or manager. On the other hand, lookup tables and estimation equations alone often do not adequately represent local variability or local conditions. This report seeks to provide methods that balance user-friendliness, data requirements, and scientific rigor in a transparent and justifiable way.

The following approaches were considered for these guidelines:

- **Basic estimation equations** combine activity data with parameters and default emission factors. Default parameters or emission factors (e.g., lookup tables) are provided in the text or an accompanying appendix. Emission factors are derived from models or available measurement data. See box 1-10 for background.
- **Models** also use combinations of activity data with parameters and default emission factors. Their inputs can be ancillary data (e.g., temperature, precipitation, elevation, and soil nutrient levels that may be pulled from an underlying source), biological variables (e.g., plant diversity), or site-specific data (e.g., number of acres, number of animals). A model's accuracy depends on the robustness of the model and the accuracy of the inputs.
- **Field measurements** are actual measurements that a farmer or landowner would need to take of the soil, forest, or farm to estimate actual emissions. Soil sampling to monitor carbon is one example of field measurement. Measuring actual emissions may require special equipment that monitors the flow of gases from the source into the atmosphere, such as remote sensing equipment (and applicable underlying micrometeorological methods). This equipment is not always readily available, so field measurements are more often incorporated into other methods to create a hybrid approach. For example, a field measurement, such as a sample mean tree diameter, could be incorporated into other models or equations to give a more accurate input.
- **Inference** uses State, regional, or national factors that approximate emissions/sequestration per unit of the input. The input data are then multiplied by this factor to determine the total onsite emissions. This factor can have varying degrees of accuracy and often does not capture the mitigation practices on the farm or the unique soil conditions, climate, livestock diet, livestock genetics, or any farm-specific characteristics, unless the factors are developed with specific soil types, livestock categories, climatic regions, etc.
- **Hybrid estimation approaches** combine the approaches described above. Hybrid approaches often use field measurements or models to generate inputs used for an inference-based approach to improve the estimate accuracy.

Box 1-10. Definitions: Activity Data, Emission Factor, and Ancillary Data

- **Activity data** include data on the magnitude of a human activity resulting in emissions or removals taking place during a given period.
- An **emission factor** is a coefficient that quantifies the emissions or removals of a gas per unit of activity.
- **Ancillary data** are additional data needed to support the selection of activity data and emission factors for the estimation and characterization of emissions.

Source: IPCC, 2019.

1.4.1 Selection of Most Appropriate Method and Management Practices to Include

This revised report reflects the current state of the science to include new methods and data sources. Specific updates to the methods are provided in the chapters and documented in table ES-1.

In drafting the methods for this report, the authors considered several selection criteria:

- **Transparency.** The assumptions and methodologies should be clearly explained to help users replicate calculations. Transparency of inventories is fundamental to the success of the process for the communication and consideration of information (UNFCCC, 2000).
- **Accuracy.** Estimates should be accurate in the sense that they are systematically neither over nor under true emissions or removals, as far as can be judged, and that uncertainties are reduced as far as practicable (UNFCCC, 2000).
- **Consistency.** The methods used to generate inventory estimates should be internally consistent in all their elements and the estimates should be as consistent with the original methods as the science allows. Consistency is an important consideration in merging differing estimation techniques from diverse technologies and management practices.
- **Comparability.** For the methods to be comparable, the estimates of emissions and sequestration being reported by one entity must be comparable to the estimates being reported by others (UNFCCC, 2000). Consequently, in general, the methods specify one method for any technology or management practice (i.e., users do not choose from a menu of methods). In some cases, the authors provided separate methodologies only to allow users to estimate emissions based on differing levels of detail for input data.
- **Completeness.** The methods must account for all sources and sinks, as well as all GHGs to the greatest extent possible. Completeness also means full coverage of sources and sinks under the control of the entity. Completeness is an important consideration to be balanced with ease of use in reporting appropriately for an entity that may have a minor activity or an activity with severely limited data availability (UNFCCC, 2000).
- **Cost-effectiveness.** The costs and benefits of additional efforts to improve inventory estimates or reduce uncertainty must be weighed against the efforts' benefits. For example, there is a balance between the costs and benefits of additional efforts to reduce uncertainty.
- **Ease of use.** The user interface and underlying data requirements must not be impractically complex.

The authors evaluated updated sources to reflect current science, including the *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories*. Any IPCC methods that are used in this report are classified according to the system of methodological tiers developed by the IPCC, which is based on the complexity of different approaches for estimating GHG emissions (see box 1-11).

The methods range from the simple Tier 1 approaches to the most complex Tier 3 approaches. Higher tier methods, particularly Tier 3 methods, are expected to reduce uncertainties in the emission estimates if sufficient activity data are available and the methods are well developed and calibrated as demonstrated with adequate testing (IPCC, 2019).

Box 1-11. IPCC Tiers

- Tier 1 represents the simplest methods, using default equations and emission factors provided in the IPCC guidance.
- Tier 2 uses default methods, but emission factors that are specific to different regions.
- Tier 3 uses country-specific estimation methods, such as a process-based model.

The report authors used the following selection criteria in confirming or updating management practice to include the methods:

- The science reflects a mechanistic understanding of the practice's influence on an emission source.
- Published research (including international studies involving management, climate, and soils similar to those in the United States) supports a reasonable level of repeatability and consistency, and the response of emissions to the given practice is understood and quantifiable.
- The authors agreed the exclusion of this method would make the sector incomplete and there is strong enough evidence that the method will hold up for this practice for at least the next 5 years.

Some practices did not fulfill these criteria, and those practices were cited as areas that need more research. These research gaps are intended to become priority focus areas for agriculture and forestry climate change research by USDA, nongovernmental organizations, universities, and other research institutions.

1.4.2 Uncertainty

Limitations and data gaps exist in the methods to estimate emissions at the entity scale. The uncertainty range for each GHG estimate communicates the level of confidence that the estimate reflects the true GHG emissions or removal between the biosphere and the atmosphere. The uncertainty associated with GHG emissions and reductions estimates may have important implications for farmer and landowner decision making; in particular, a farm, ranch, or forest landowner or manager may be more inclined to invest in management practices that reduce net GHG emissions if the uncertainty range for an estimate is low, meaning higher confidence in the estimate. As new data become available and methods are developed, the uncertainty in emissions estimates will decline.

This report includes approaches for quantifying uncertainty in the estimated net emissions for each method. In general, a Monte Carlo approach (see chapter 8) should be used to estimate the uncertainty for the methods; it is currently the most comprehensive approach. Monte Carlo analyses require the use of statistical techniques to produce prediction intervals (i.e., the probability density function, or PDF) for the GHG emissions estimate.

The report also describes uncertainty assessment methods for each source as well as for the total estimate. Not all methods allow for a reliable statistical estimate of uncertainty due to a lack of data. In some cases, the authors used expert judgment to delineate estimated uncertainty bounds. In other cases, the report simply notes that more data are needed to reliably estimate uncertainty.

1.5 Chapter 1 References

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Chapter 2
Considerations When Estimating Greenhouse Gas Fluxes in Agriculture and Forestry

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Acronyms, Chemical Formulae, and Units

CH_4	methane
CO_2	carbon dioxide
CO_2-eq	carbon dioxide equivalents
CrIS	Cross-track Infrared Sounder
FIA	Forest Inventory and Analysis
FTIR	Fourier transform infrared
GHG	greenhouse gas
GWP	global warming potential
HMTLS	handheld mobile terrestrial laser scanning
HWP	harvested wood products
IPCC	Intergovernmental Panel on Climate Change
LiDAR	light detection and ranging
N_2O	nitrous oxide
NAIP	National Agriculture Imagery Program
NH_3	ammonia
NO	nitric oxide
OpTIS	Operation Tillage Information System
PALSAR	Phased Array type L-band Synthetic Aperture Radar
PDF	probability density function
SF_6	sulfur hexafluoride
STLS	static terrestrial laser scanning
sUAS	small unmanned aerial system
TDL	tunable-diode laser
TROPOMI	TROPOspheric Monitoring Instrument
UAS	unmanned aerial system
USDA	U.S. Department of Agriculture

2. Considerations When Estimating Greenhouse Gas Fluxes in Agriculture and Forestry

The methods provided in this report depend on standard definitions and common estimation elements for all emission sectors. This standardization ensures that landowners or managers can accurately inventory their direct greenhouse gas (GHG) emissions and removals and make comparisons across years; management practices; or farms, ranches, or forests. This chapter provides standard definitions, explains the steps in the estimation process, and provides other information to help landowners and managers understand the estimation elements to include and the methods to use.

2.1 Standard Definitions

2.1.1 Entity

The methods in this report allow GHG source and sink quantification at an entity scale. For this report, an entity is defined as all activities occurring on all tracts of land under the ownership and or management control—now and for the foreseeable future—of a farm, ranch, forest landowner or manager.

This is not a policy or regulatory definition; it is provided to help the landowners and managers determine what practices they should include in their GHG estimations. The definition is intentionally broad and will depend on the landowner's input data for the estimation methodologies. Any policy, registry, or market will provide its own, narrower definition.

2.1.2 Emissions and Sinks

This report uses "emissions," and some related terms, as follows:

- **Emissions:** The calculated total mass of GHG released over a specified period. Emissions can be direct or indirect. Direct emissions are caused by an entity's activities—for example, manure managed in solid storage stacks produces direct nitrous oxide emissions. Indirect emissions are caused by the activity but removed by space or time—for example, nitrogen volatilization and subsequent deposition, or leaching and runoff of manure, produces indirect nitrous oxide emissions.
- **Carbon dioxide (CO_2) equivalents:** GHG emissions are often presented in units of CO_2 equivalents (CO_2-eq), calculated by multiplying the amount of a GHG by its global warming potential (see section 2.2.4.1).
- **GHG sequestration, sinks, and removals:** Sequestration is the process of removing GHG from the atmosphere through capture and storage. For this report, GHG removals are the calculated total mass of GHG removed from the atmosphere. (In the context of forest management, "removals" can also refer to the volume of trees felled or removed from the forest during a timber harvest or treatment, but for this report refers to the mass of GHG removed from the system in question.)
- **Flux:** The change in GHG mass within system boundaries (see section 2.2). GHG flux is normally reported for discrete time steps—such as annually, daily, or hourly—in negative numbers (indicating removals/sequestration) or positive numbers (indicating emissions).

- **Carbon stock:** The mass of carbon stored at a given time in a carbon pool (including aboveground biomass, belowground biomass, dead wood, litter, and soil organic and mineral carbon pools).

2.1.3 Activity and Ancillary Data

All of this report's technical chapters describe the activity data needed to estimate GHG emissions or carbon removals. Activity data include data on the magnitude of a human activity resulting in emissions or removals taking place during a given period (IPCC, 2019). Some available methodologies or approaches to collect activity data are presented in appendix 2-A.

Ancillary data are additional data needed to support the selection of activity data and emission factors. Examples of ancillary data include temperature, precipitation, elevation, and soil nutrient levels from references.

2.1.4 Emission and Removal Factors

An emission or removal factor is a coefficient that provides quantitative estimates of emissions or removals of a gas per unit. Emission and removal factors reflect the net flux of GHGs associated with a land-use transition or management activity. For example, for forest clearing, the emission factor is the summation of the carbon emitted from all included carbon pools for the type of forest cleared. An emission factor describes emissions (i.e., total carbon emitted during a deforestation event), whereas a removal factor describes removals/sequestration (i.e., carbon accumulated through a forest management activity).

Emission or removal factors may be derived from existing sources, such as published literature and emission factor databases (e.g., the Intergovernmental Panel on Climate Change [IPCC] Emission Factor Database[1]), or developed from inventories. The latter approach calls for comprehensive, regular field sampling using locally calibrated models, which can be a large commitment of resources and time. When choosing emission or removal factors, an entity should balance needs for precision, accuracy, and lower uncertainty (see section 2.1.5) with costs and long-term goals for GHG accounting. In most cases, emission and removal factors are used in more simplified estimation methodologies (such as IPCC Tier 1 or Tier 2), not more advanced (IPCC Tier 3) ones.

2.1.5 Uncertainty, Accuracy, and Precision

IPCC (2019) provides the following definitions:

- **Uncertainty:** Lack of knowledge of the true value of a variable that can be described as a probability density function characterizing the range and likelihood of possible values. Uncertainty depends on the analyst's state of knowledge, which in turn depends on the quality and quantity of applicable data as well as knowledge of underlying processes and inference methods.
- **Accuracy:** A relative measure of the exactness of an emission or removal estimate. Estimates should be accurate in the sense that they are systematically neither over nor under true emissions or removals, so far as can be judged.
- **Precision:** Closeness of agreement between independent results of measurements obtained under stipulated conditions. Better precision means less random error.

[1] https://www.ipcc-nggip.iges.or.jp/EFDB/main.php

2.2 System Boundaries

System boundaries define the scope of GHG estimation. The boundaries are critical to the interpretation of results and define important aspects of the analysis (e.g., number of management practices, number of GHGs, timeframe, geography). Entities should consider four types of system boundaries, which are discussed in the following sections.

System boundaries should include the GHG emissions and carbon sequestration occurring (or established) onsite for the source category and management practice in question. For example, this report does not address indirect offsite land-use changes or biogenic GHG flux related to subsequent use of agricultural or forestry outputs (e.g., food processing, pulp and paper manufacture, biomass combustion). However, it does address certain offsite carbon storage considerations (e.g., flow of harvested wood into harvested wood products, or HWPs) to maintain consistency with national inventory efforts.

2.2.1 Physical Boundaries

The physical boundary is the geographic area in which project activities take place. Physical boundaries address the area and the management practices to consider in estimations. Because there can be a number of scenarios for setting boundaries for emissions and sequestration estimation, clarity, and consistency are important. For example, consider answers to the following questions when defining physical boundaries:

- What constitutes an entity or a farm/ranch/forest operation?
- What activities are associated with that entity? For example, does fertilizer use on a farm include manufacturing processes and fertilizer delivery?
- How should a larger entity with multiple land uses (such as grazing land and cropland) within its boundaries be subdivided?
- How should management practices be associated with the most relevant methods (including any guidance on size limits, what constitutes management, and how to address changing land uses)?

Within the boundaries of an entity, there may be areas of cropland, grazing land, animal production, forestland, wetlands, settlements, and/or other land. The physical boundaries of each of these emission sectors must be identified.

2.2.1.1 Cropland Physical Boundaries

Croplands are areas used for producing adapted crops for harvest, including:

- Cultivated and noncultivated land
- Agroforestry area (e.g., alley cropping, windbreaks) where the primary activity is crop production
- Land that is fallow or set aside, such as lands in a conservation reserve program
- Areas of hay and pasture that are managed in a rotation with other crops
- Wetlands (including drained wetlands and hydric soils) where the primary activity is crop production

General guidance for delineating cropland physical boundaries:

- Delineate areas of cropland, roads, and railroads.
  - Evaluate areas of cropland as fields or groups of fields for which the basic rotations and management practices are similar. Use the methods in chapter 3.
  - Consider roads and railroads through the cropland as settlements and exclude them from the cropland area.

2.2.1.2 Grazing Land Physical Boundaries

Grazing lands are areas primarily used for grazing animals (not as part of a rotation with other crops). The plant cover is composed principally of grasses, grass-like plants, forbs, or shrubs suitable for grazing and browsing. Grazing lands may include:

- Pastures or native rangelands
- Savannas, tundra, or deserts
- Woody plant communities of low forbs and shrubs that do not meet the criteria for forestland
- Land managed with agroforestry practices (e.g., silvopasture) where the stand or woodlot does not meet the criteria for forestland and where the primary tract of land is used for grazing livestock
- Some wetlands (including drained wetlands and hydric soils) where the primary tract of land is used for grazing livestock

General guidance for delineating grazing land physical boundaries:

- Delineate areas of grazing land, roads, and railroads.
  - Delineate grazing lands with similar stocking rates and management practices as contiguous areas. Use the methods in chapter 3.
  - Consider roads and railroads through the grazing land as settlements and exclude them from the grazing land area.
- For grazing animals, follow the relevant methods in chapter 4.
- Integrate methods where lands match the definition for both grazing land and forestland. For example, if any active management is focused on enhancing tree growth and timber production, identify these areas as forestland and integrate the methods to account for the impact of grazing management on the forestland.

2.2.1.3 Animal Production Physical Boundaries

Animal production systems raise animals to produce commodities for human consumption (e.g., meat, milk, eggs, wool). Although animal production is not necessarily a spatially defined activity, it must be considered as part of the physical boundary of the operation. Areas to consider are:

- Emissions from the animals themselves through enteric fermentation
- Emissions from housing
- Emissions from the management of manure

Be aware that GHG emissions from animal production vary greatly depending on species, growth stage, diet, and manure storage and management. Timing is also a challenge because emissions per animal change dramatically as a young animal grows and matures, as feedlot cattle are finished, or as dairy cows cycle between gestating and lactating.

General guidance for delineating animal production physical boundaries:

- Use the methods for animal production in chapter 4.
- In most cases, it may be necessary to estimate emissions for a herd using average weight, average age, and other representative characteristics.
- In other cases, it will be necessary to generalize by seasons. For example, manure management can be different in winter than summer.
- Apply assumptions consistently across the herds and timeframes.
- In some cases, such as for manure applied to cropland under the ownership and or management control of the entity, chapter 3 methods will also be relevant.

2.2.1.4 Forestland Physical Boundaries

Forestlands are lands that are at least 120 feet (36.6 meters) wide and 1 acre (0.4 hectare) in size with at least 10 percent tree crown cover (or equivalent stocking level) and trees able to reach at least 6.6–16.4 feet (2–5 meters) at maturity in situ, including land that formerly had such tree cover and that will be naturally or artificially regenerated.

Forestland can include:

- Closed (trees of various stories and undergrowth covering much of the ground) or open (continuous vegetation cover in which tree crown cover exceeds 10 percent) forest formations
- Land primarily used for woody biomass production or that is tree-covered and managed for recreational or conservation purposes
- Agroforestry and silvopasture areas where the primary management objective is forest-related production
- Wooded or forested wetlands managed primarily as forests and woodlands
- Managed systems, such as woodlots and plantations

General guidance for delineating forestland physical boundaries:

- Follow the forestland methods in chapter 5.
- Delineate areas of forestland, unimproved roads and trails, streams, and clearings in forest areas.
  - Evaluate areas of unimproved roads and trails, streams, and clearings in forest areas wider than 120 feet (36.6 meters) or larger than 1 acre (0.4 hectares) as settlements and exclude them from the forestland area.
  - If areas of forestland are in an urban setting, evaluate them as settlements.
- Delineate forest tracts so that each one includes trees of a similar stand age and species mix and the entire entity is under one uniform set of management practices.
- If an entity includes trees outside clearly defined forests (such as orchards, vineyards, farmstead shelterbelts, and field windbreaks), it may be useful to blend methods (for

example, cropland methods from chapter 3 and forest methods from chapter 5) or evaluate individual trees or small stands of trees using chapter 5 methods.

- Account for emissions from HWPs, even though they may be moved outside the operation boundary, since harvested wood moves through several long-term carbon pools at differing rates of decay.

2.2.1.5 Wetland Physical Boundaries

Wetlands are areas with hydric soils, native or adapted hydrophytic vegetation, or a hydrologic regime where the soil is saturated during the growing season in most years. They can include:

- Swamps, marshes, bogs
- Undrained forested wetlands, grazed woodlands and grasslands, impoundments managed for wildlife, and lands being restored to a wetland after conversion to a nonwetland condition
- Engineered wetlands (e.g., stormwater detention ponds, constructed wetlands for water treatment, farm ponds, or reservoirs)
- Riparian areas of natural lakes and streams

General guidance for delineating wetland physical boundaries:

- If a wetland area has been included in one of the other categories, its management will be captured in the estimation for that category. If not, identify the area as either a managed wetland or a natural, unmanaged wetland and use chapter 6 methods.
- Do not include natural, unmanaged wetlands—that is, naturally occurring wetlands that are not being actively managed to increase productivity or provide other environmental services. Categorize these wetlands as “other lands” as defined below.
- Use the chapter 6 estimation methods for emissions from palustrine wetlands influenced by management options such as water table management, timber or other plant biomass harvest, and management with fertilizer applications.

2.2.1.6 Settlements Physical Boundaries

Settlements are areas of developed land consisting of units of 0.25 acres (0.1 hectares) or more, including two broad categories:

- Land where the entity manager imposes management decisions (e.g., livestock feed yards, dairy barns, poultry houses, manure piles)
- Land where the manager does not regularly impose management decisions that affect carbon balances (i.e., homes, yards, driveways, workshops, roads, railroads, and parking areas).

Guidance for delineating settlements physical boundaries:

- Include only the areas with GHG flux implications.
    - Use the livestock and manure management methods presented in chapter 4 for animal production areas.
- Do not include areas without GHG flux implications, such as homes, yards, driveways, workshops, roads, railroads, and parking areas.

2.2.1.7 Other Land Physical Boundaries

Any land that is actively managed in a way that affects biomass growth or otherwise affects production-related GHG emissions should have been captured within the boundaries defined for the land-use categories listed above. Categorize any remaining land as “other lands” or “unmanaged land,” and do not consider them in the estimation. Other lands can include:

- Wetland and developed areas without active management (e.g., unmanaged wetlands and unmanaged settlements)
- Other areas within the entity boundary that represent barren, mined, abandoned, or otherwise unmanaged land (e.g., bare soil, rock, ice)

Land cover change is a variation from year to year in what is growing on a parcel of land, such as rotating corn and soybean crops, and is not considered land-use change. Do not consider land cover changes in the GHG estimation.

In contrast, land-use change is a fundamental shift in purpose or production of a parcel. Land-use change should be accounted for in the GHG flux estimate. Land-use change can include the following events:

- Part of a cropland field is converted to an animal feedlot.
- Shelterbelt or riparian trees are planted onto former cropland.
- Abandoned land reverts to grazing land or forestland cropping.
- Cropland reverts to forest production or vice versa.

Guidance for delineating land use physical boundaries:

- Use the methods in chapter 7 to account for land-use change in the annual GHG flux as the impact (either positive or negative) on biomass and soil carbon.
- Identify parcels where the land use has changed. This may require delineating new parcel boundaries or dissecting one parcel into several parcels with more than one management strategy.

2.2.2 Temporal Boundaries

The temporal boundary is the timeline in which the activity is taking place. It is important to account for short- and long-term management decisions that have implications for carbon balances and address the movement of spatial boundaries over time and with land-use changes. The methods in this report provide a means of annual accounting and reporting of GHG fluxes. Annual changes are easy to quantify for some emissions, but more difficult for others. For example, it may be necessary to estimate carbon stored in trees over a longer period and then convert the change to an annualized estimate.

Box 2-1. Temporal Scale

The report methodologies assume an accounting period of 1 calendar year (i.e., 365 days) when estimating annualized emissions in a particular sector or source category.

Management decisions also affect the accounting time horizon. For example, a forest management plan might call for timber harvest. In the harvest year, the annual accounting will reflect a loss of standing live and/or standing dead carbon stocks, yet the longer-term management strategy could cause a net increase in total carbon stocks.

A manager might also take corrective action or temporarily deviate from a long-term management plan. For example, a cropland manager might have adopted a no-till management strategy, but after several years need to use tillage for 1 year because of weather, pests, or other extenuating circumstances. In this case, the methods used should be sensitive enough to capture the GHG impact of the management plan deviation.

2.2.3 Activity Boundaries

Activity boundaries distinguish which activities within an entity are subject to GHG accounting. The accounting in this report focuses on land-based activities such as tillage and harvesting, not on GHG emissions related to fossil fuel use. Thus, emissions from tractor fuel or fuel used in crop drying are not counted, nor are the energy inputs required to manufacture fertilizer or farm tools or to heat farm buildings. The activity boundaries do not include emissions from fossil fuel use.

Methods in this report do not constitute a life cycle assessment. The exception is the chapter 5 HWP method, which includes stages of HWPs from forest harvesting to product manufacturing.

2.2.4 Material Boundaries

Material boundaries define which materials—for this report, which GHGs—are considered in the estimate. It is important to determine initially which gases are included and which are not. It is also important to determine how much freedom the user has in where these boundaries lie to ensure that a management change that reduces emissions in one sector does not inadvertently cause emissions to increase outside the reported boundaries.

2.2.4.1 Global Warming Potentials

Global warming potentials (GWPs) are important when considering GHGs. Warming potential correlates to how much heat the molecules absorb in the atmosphere, which drives climate change. A GWP is a ratio: the radiative forcing (or heating effect) that would result from the emission of 1 ton of a gas, over a defined period, versus the forcing from the emission of 1 ton of CO_2 over the same period. In this report, the defined period is 100 years and the GWP is the energy 1 ton of a gas will absorb over 100 years, relative to 1 ton of CO_2.

Multiplying the mass of a GHG by its GWP produces results in units of CO_2-eq. While CO_2 has a GWP of 1, methane (CH_4) is more potent and nitrous oxide (N_2O) is significantly more potent; see table 2-1 for GWP values applied in this report. These GWPs are from the IPCC Fifth Assessment Report (IPCC, 2013). Note that policies, registries, or markets may use other GWPs.

Table 2-1: Global Warming Potentials Used in the Report

GHG	Chemical Formula	Lifetime (Years)	GWP[a]
Carbon dioxide	CO_2	Variable	1
Methane	CH_4	12.4	28
Nitrous oxide	N_2O	121	265

[a] Source: IPCC (2013). GWPs used have a 100-year time horizon, in accordance with the IPCC Fifth Assessment Report (IPCC, 2013).

Emissions and removals of the main GHGs—CO_2, CH_4, and N_2O—are accounted for in the estimation methodologies for the croplands, grazing lands, wetlands, animal production, forestry, and land-use change sectors. This report presents emissions and sequestration values in terms of the mass (not volume) of each gas, using metric units (e.g., metric tons of CH_4).

2.2.4.2 Direct and Indirect Emissions

The methods in this report focus on the direct emissions resulting from management decisions made within the entity boundaries. Indirect emissions related to inputs into the entity are excluded from this report, since the manufacturer producing the inputs would account for them. There are notable exceptions involving cases when management decisions for an operation have a specific influence on emissions leaving the entity's boundary. For example, this report includes:

- Indirect nitrogen emissions within the operation that are carried offsite via volatilization, erosion, or leaching and contribute to N_2O emissions offsite.
- An assumption that grains or other agricultural commodities are consumed relatively quickly, resulting in no net gain or loss for GHG accounting. (HWPs are somewhat different: much of that harvest will end up in long-term carbon pools as structures, furniture, or other wood products or in landfills.)

2.3 Estimation Process Overview

2.3.1 Estimation Scenarios

Some entities may wish to develop basic estimates of the current management practices. For example, an entity might develop an entity-level GHG inventory. This estimate would represent the baseline or "business as usual" estimate. This scenario would have a set timeframe with current business practices defined and included.

Other entities may wish to use these methods to estimate emissions or GHG removals from practices that will be maintained over a period of time or from altering management practices.

2.3.1.1 "Basic" Estimate

This option serves the entity seeking to estimate the GHG flux from maintaining a current management practice. Maintenance is very broadly defined and can include no active management. This estimate would be the baseline scenario or status quo for a given entity. For example, a livestock producer would include the number of animals currently housed, the current diet and feed situation, as well as the current housing and manure management practices.

For a forest (see chapter 5), a basic estimate could describe a forest parcel maintained as a forest or even a planned harvest and subsequent changes or stored carbon over time. Typically, the baseline is the current carbon stock or the carbon stock at a specified prior year. However, in situations where the carbon stocks are changing, the baseline is computed over time as the forward-looking carbon stocks that would occur in the absence of the project or intervention.

2.3.1.2 Estimated Impact of a Management Change

To estimate the impact of a change in management practice, the entity manager needs to produce estimates for both the baseline scenario (see section 2.3.1.1 above) and the management scenario. The same method should be used for both estimates, recognizing there will be assumptions about the future for the management scenario. In the case of forests, assumptions on forest growth might be needed; these could be based on basic biological principles and historical monitoring of forest dynamics.

The difference between the two scenarios represents the net benefit from switching management practices.

2.3.2 Basic Steps for Estimation

Chapter 1 describes the general principles of GHG inventories and carbon accounting, but practically speaking there are four basic steps to estimating GHG fluxes using the methods in this report. These steps are described below.

2.3.2.1 Define the Project

The first step involves establishing which activities will be accounted for in the estimation, defining the boundaries in which these activities take place, and defining a baseline scenario that articulates what would most plausibly have happened in the absence of a planned activity or project intervention.

- **Identify activities.** One project may feature a range of activities, and it is important to clearly delineate them to set up separate accounting frameworks and consider interactions and potential for double-counting. The combined impact of these activities would be needed to estimate the net GHG flux. Examples:
    - An entity managing forested land that includes both new replanted area and the existing forest might consider methodologies for two “activities”: reforestation and extended rotation.
    - An entity implementing no-till may need to increase fertilizer use. Both activities need to be considered.
- **Define boundaries.** There are several types of boundaries to consider, as described in section 2.2.
- **Describe the baseline scenario.** The baseline represents the total GHG or carbon emissions or removals anticipated in the absence of the planned activity or project. The baseline should reflect the most plausible scenario for the absence of the planned project intervention. It is best practice to fully document the baseline scenario, articulating management practices and general conditions in the absence of the project intervention. See section 2.3.1 for details on estimation scenarios.

2.3.2.2 Decide on the Level of Accuracy and Precision, Assess Data Availability, and Identify Calculation Approach

The methods in this report accommodate a range of user needs, data availability, and GHG accounting experience. As such, the guidance allows for different desired levels of accuracy, precision, and accessibility while ensuring accounting consistency. However, consistency should not come at the expense of enhanced precision or methodological integrity. Improvements in accounting methods and data can be anticipated over time. Therefore, it is important to document assumptions made and data used so that estimates can be updated if new methods or data become available.

2.3.2.3 Collect/Assemble Data

Based on the chosen approach, collect or assemble data and quantify results. More detail can lead to more precise GHG estimates, but even broad generalizations can result in a GHG estimate. The objective is to obtain accurate, consistent estimates over time at a reasonable level of effort and cost. Depending on the method chosen, this could simply involve assembling basic information on the nature and area of planned activity—or it could require establishing a network of sample plots and collecting inventory data on key variables over time.

2.3.2.4 Produce Estimates

Using the appropriate method and required data, calculate the GHG flux estimate. Document the data, assumptions, methods, and boundaries used to develop the estimates to help ensure useful and credible results.

2.4 Chapter 2 References

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Appendix 2-A: Background Information on Field-Scale Carbon and GHG Detection Technologies

This appendix summarizes currently available and in-development field-scale carbon and GHG detection technologies. It puts these in three categories:

- Remote sensing techniques are primarily used to gather activity data used in emissions estimates but may also directly measure emissions using measurement techniques.
- Measurement techniques are used to directly measure emissions.
- Micrometeorological methods use environmental parameters and ultimately require mathematical equations to estimate emissions.

Note that this appendix is not intended to serve as a complete compendium of all technologies or techniques. It also does not compare the discussed technologies; these comparisons are available in other literature (e.g., U.S. EPA, 2018).

2-A.1 Remote Sensing

Remote sensing techniques use sensors at a distance (typically aboard satellites or aircraft) to acquire information. These techniques can be used to collect satellite images and aerial photographs that can provide information such as the presence and location of specific crops. In addition, they can be used to measure distances and temperatures. They can also directly detect and record atmospheric concentrations of GHGs.

Unmanned aerial systems (UAS) and small UAS (sUAS) are aircraft that are flown either remotely or autonomously. The use of UAS and sUAS for remote sensing allows for more precise data collection on a smaller scale. However, unlike satellites, UAS are limited by local air traffic restrictions (Shaw et al., 2021). UAS and sUAS can both use light detection and ranging (LiDAR) or aerial imagery technology (see sections 2-A.1.1 and 2-A.1.2).

The following subsections describe currently available and in development field-scale remote sensing techniques.

2-A.1.1 LiDAR

LiDAR uses a pulsed laser to measure distances to Earth (NOAA, 2021). A laser source emits light pulses, which reflect off objects of interest before returning to the system's sensor. LiDAR sensors can be mounted on satellites or aircraft (including UAS) or used in terrestrial applications.

LiDAR can be used to gather structural characteristics and data for agricultural and forestry applications (Lister et al., 2020). For example, it can be used for field mapping, monitoring forest canopy changes, determining soil types, and identifying grazing land. Airborne LiDAR has been used to map forested riparian buffers and quantify vegetation height, canopy cover, and corridor width to understand the impact of adjacent land use types (Wasser et al., 2014). LiDAR is used along with other data sources, such as Forest Inventory and Analysis (FIA) data. Together, LiDAR and FIA data can better estimate canopy cover, estimate tree heights, and inform models of forest volume or biomass and land cover class (Lister et al., 2020).

Static terrestrial laser scanning (STLS) can measure an entire environment from a fixed point using LiDAR. This method can be useful in forestry contexts to measure wood volume, tree height or diameter, and structural characteristics below the canopy, and to estimate biomass. Handheld mobile terrestrial laser scanning (HMTLS), developed for rough terrains, is an effective alternative to the time-consuming and costly STLS method. HMTLS has been demonstrated to be a precise, effective method for calculating tree diameter (Stal et al., 2021). A handheld LiDAR system has been used to measure grass heights, an indicator of growth conditions (Obanawa et al., 2020).

LiDAR can also be used to directly measure GHG emissions through integrated path differential absorption, which uses scattered laser signals from an aircraft or satellite to measure weighted vertical column concentrations of GHGs; these can then be converted into the emission rate (Kiemle et al., 2017).

As LiDAR develops further, it can improve data collection efforts and eliminate the need for certain manual measurements.

2-A.1.2 Digital 3D Aerial Imagery

Structure from motion (SfM) is a process for estimating a 3D image based on overlapping 2D images (Gatziolis et al., 2015; NOAA, n.d.). SfM is based on a type of algorithm—scale invariant feature transform—that automatically matches an object or land marker within photographs, even if the photographs vary in scale or angle, which is key to the overlapping that creates the 3D image (Gatziolis et al., 2015; Nissen et al., n.d.; Iglhaut et al., 2019). Because they provide higher temporal and spatial resolution than satellites, UAS can be used to derive 3D models of vegetation height and topography using SfM (Sankey et al., 2019). A UAS with a relatively basic camera can use SfM to provide an affordable alternative to terrestrial LiDAR (Gatziolis et al., 2015).

The National Agriculture Imagery Program (NAIP) aims to update the aerial imagery acquired during the U.S. growing seasons, produced about every 3 years (USDA, n.d.). Lister et al. (2020) describe how NAIP imagery is used in the Image-based Change Estimation project, which offers updates on land cover changes faster than during the FIA cycle (5 to 10 years).

2-A.1.3 Satellite Instrumentation

The Cross-track Infrared Sounder (CrIS) is a type of Fourier transform spectrometer designed to provide a vertical profile of Earth's atmospheric temperature and water vapor; it is currently onboard the Suomi National Polar-orbiting Partnership satellite (Bloom, 2001; O'Carroll and Leslie, 2012). CrIS also measures atmospheric gas concentrations: these gases absorb infrared light, which CrIS's sensor detects and translates to a concentration along the vertical path (Keesey, 2016). The sensor's data records are available for download (NOAA, 2018). Researchers have used CrIS data to verify modeled emissions estimates (Whaley et al., 2018).

The Phased Array type L-band Synthetic Aperture Radar (PALSAR) is one of three major remote sensing instruments on the Advanced Landing Observation Satellite (JAXA, 2008). It uses the L-band frequency (the microwave range) for day and night land observation (ASF, 2022; JAXA, 2008). NASA and the Indian Space Research Organization also have a synthetic aperture radar (called the NASA-ISRO SAR, or NISAR), with a 3-year mission, that operates in both L-band and S-band frequency and offers resolution of 3 to 10 meters (NASA, n.d.). Both of these instruments provide satellite imagery that can be used to identify forest cover and ultimately to estimate emissions. For example, Hamdan et al. (2016) described using PALSAR imagery to estimate the rate of deforestation and subsequent CO_2 emissions.

2-A.2 Measurement Technologies

Measurement technologies are chosen depending on the goals of the quantification as well as known underlying conditions and available resources.

2-A.2.1 Chamber Systems

The following sections describe enclosure-type measuring techniques in which the area or animal to be monitored is kept in an enclosure to allow for emissions measurements without influence of outside air. These systems can be disruptive to the environment, either to the animal or the normal state of the landscape where the measurements are taken.

Flux Chambers

Flux chambers are used to isolate emitting surfaces such as fields or pen surfaces to measure for gases such as CO_2, CH_4, N_2O, and nitric oxide (NO) (Oertel et al., 2016; Cole et al., 2018). Gas sensors such as gas chromatography or infrared spectrometry can be used with this method to analyze the samples (Oertel et al., 2016).

As described by Oertel et al. (2016), flux chambers can be nonflow or flow chambers:

- Nonflow, or closed, chambers can be either static or dynamic. In a static closed chamber, samples are taken from accumulated air in the chamber. In a dynamic closed chamber, samples are either analyzed externally before being pumped back into the system or analyzed inside the chamber continuously.
- In flow, or open, dynamic chambers, gas concentration is analyzed at the air inlet and outlet to calculate gas fluxes. Flow chambers are more expensive than nonflow chambers but are better in dry and hot conditions due to temperature and pressure gradients.

Wind Tunnels

Wind tunnels have been used to measure emissions from pens and retention ponds. The area to be monitored is partially enclosed, with the ends of the enclosure opened to allow for forced or natural air movement. The concentration of gases and the air flow rate are measured at both ends of the wind tunnel to calculate the flux rate. Typically, this practice is more suitable for comparing treatments or assessing relative emission rates than quantifying GHGs (Cole et al., 2018).

Respiration Chambers

Respiration chambers are used in measurements of enteric CH_4 from cattle, specifically to measure energy metabolism and gas production. Modern modifications to respiration chambers also allow the measurement of manure emissions (Chiavegato et al., 2015; Stackhouse-Lawson et al., 2013). In respiration chambers, a chamber houses the animal, the ducting and flow system, and the gas analyzer instruments (Arceo-Castillo et al., 2021). Open circuit, indirect systems are most common and involve the measurement of incoming and outgoing gas concentrations as negative pressure pulls air out of the chamber (Cole et al., 2018).

While this method allows for the accurate measurement of enteric emissions from individual animals, it limits the animal's activity and can only be used for short periods. Animals also need training and may have a smaller dry matter intake than in normal situations (Cole et al., 2018).

A less expensive option for respiration chambers is the head-box system. A system used by Ortega et al. (2020) includes a pen for the animal that allows for feeding, air circulation, manure collection, and gas collection. GreenFeed, a brand of head-box systems, has a chamber that takes gas measurements when the animal places its head inside to eat (C-Lock, 2022). Typically, the feed is provided in small quantities to encourage animals to provide multiple measurements each day (Hristov et al., 2015). The system provides a summarized report for calculated CH_4 and CO_2 fluxes (C-Lock, 2022).

2-A.2.2 Open-Path Analyzers

Open-path analyzers, such as infrared spectrometers, have been used in agricultural contexts. These analyzers use light beams to measure gas concentrations as an average over the path of the light (Cole et al., 2018). With this method, continuous, real-time measurements are possible in the field because the instruments are portable. However, these instruments often need careful maintenance and calibration (Cole et al., 2018).

Infrared absorption spectroscopy requires instrumentation to cause molecules to vibrate (radiation source), ultimately absorb light, and transform and process that signal (detector and processer) (Chair and Secretary, 2017). Common instruments that use infrared spectroscopy are:

- A Fourier transform infrared (FTIR) spectrometer provides real-time measurements of gaseous compounds using an infrared beam emitted from a mounted instrument (U.S. EPA, 2018). One benefit of FTIR spectroscopy is that multiple gaseous compounds can be monitored at the same time (U.S. EPA, 2018).
- A tunable-diode laser (TDL) absorption spectroscopy instrument relies on diode lasers for the light source and can be used in meteorological methods to estimate concentrations of gaseous species (Pattey et al., 2004; Edwards et al., 2003). TDL is highly sensitive, provides a fast sampling rate, and has been used to analyze for N_2O and CH_4 over agricultural fields (Pattey et al., 2004). TDL is generally used when only one or two compounds are targeted and is limited to a relatively small list of compounds that can be measured (U.S. EPA, 2018).

2-A.2.3 Sulfur Hexafluoride (SF_6) Method

The SF_6 method can be used to measure enteric CH_4 emissions from individual cattle. A cylindrical tube with permeable walls releases SF_6 at a predetermined rate into an animal's rumen, and the gases released from the animal's nostrils are collected via tubing attached to mounted canisters. When the canisters are full, they are removed and analyzed for CH_4, CO_2, and SF_6 using gas chromatography and electron capture and flame ionization detectors (Grainger et al., 2007). With the SF_6 method, animals have a near-normal environment. However, background gas concentrations in barns can affect the results (Cole et al., 2018). One study recommended using the SF_6 method for grazing cattle (McGinn et al., 2006).

2-A.3 Micrometeorological Methods

Micrometeorological methods use climate parameters—temperature, wind speed and direction, net radiation—and mathematical equations to quantify emissions (Cole et al., 2018; Hicks and Baldocchi, 2020). These methods rely on the basic concept of atmospheric gas molecules' eddying motion behavior (Hicks and Baldocchi, 2020; Zaman et al., 2021). Implementing these methods requires measurements of the applicable climatic parameters, including atmospheric gas concentration (Cole et al., 2018). Therefore, these methods often need equipment such as the following (Hicks and Baldocchi, 2020; McGinn et al., 2006; Nelson et al., 2017):

- Open-path analyzers (see section 2-A.2.2) or another way to measure gaseous concentration or estimate fluxes
- Retroreflector to terminate the laser path and return the light to a receiver (U.S. EPA, 2018), if needed (depends on the instrument configuration)
- Climate parameter sensors, which must typically take measurements at the same spatial and temporal plane:
  - Anemometers to measure the speed and direction of the wind
  - Temperature sensor/gauge
  - Net radiometer to measure net radiation
  - Hygrometer to measure humidity
- Canister or tube for gas storage
- Computer and software to collate sensor data
- Power source(s) to power all equipment

The physical setup for the method depends on the theory of the method, equipment needed, and chosen location. Some methods need measurements at two different heights if they depend on the vertical changes within an air column (Nelson et al., 2017; Zaman et al., 2021). Direct micrometeorological techniques do not disturb vegetation or soil or animal habits, unlike other methods (e.g., respiration chambers); however, they can be expensive and more difficult to replicate given the relatively large land area they need (Cole et al., 2018).

Note that the following sections do not include the whole range of micrometeorological methods. Several other methods may be more appropriate for studies or projects, given the goals and limitations or project setup.

2-A.3.1 Modified Bowen Ratio

The modified Bowen ratio, or Bowen-ratio energy balance, is a commonly used flux gradient micrometeorological method with a relatively simple theoretical basis and less complex equipment (Wolf et al., 2008; Meyers and Baldocchi, 2005). The measurement of vertical differences is used to determine air-surface exchange rates and fluxes. This method has been used to measure CO_2 fluxes for till and no-till crop management systems (O’Dell et al., 2014). Air intake boxes at two different heights recorded temperature, humidity, and CO_2, measured with a nondispersive infrared gas analyzer (O’Dell et al., 2014).

2-A.3.2 Eddy Covariance (Flux Tower)

Eddy covariance is a direct micrometeorological method that requires measurements of wind speed, wind direction, and gas concentrations to ultimately determine average flux density (Baldocchi, 2014; Kumar et al., 2017). Parameters include (Meyers and Baldocchi, 2005):

- Vertical velocity
- Molar density
- Time
- Eddy flux measurement height
- Vertical distance
- Molar mixing ratio (of the gas) relative to dry air

Practical application for quantifying emissions typically uses a tower, or a pair of towers. The technique requires rapid measurements, so fast sensors are critical (Harper et al., 2011). Measurements are most accurate in a steady atmosphere, with homogeneous underlying vegetation and flat terrain. This is conducive to determine the flux over a large agricultural area. Typically, sensors in eddy covariance systems analyze for CO_2, CH_4, and N_2O gases (Kumar et al., 2017).

Several hundred flux measurement sites globally, including FLUXNET,[2] provide widespread data (Baldocchi, 2014).

2-A.3.3 Integrated Horizontal Mass Flux

Integrated horizontal flux is a mass balance method that can be used to estimate the rate of gas transfer from the ground to the atmosphere. However, it is a limited technique that does not take into account turbulent flux, like eddy covariance. Parameters include (Harper et al., 2011):

- Wind speed and direction
- Gas concentration
- Height (from the ground to the top of the gas plume)

The method is generally limited to smaller plots and also assumes emissions from the source are uniform (Harper et al., 2011; Todd et al., 2006). Todd et al. (2006) used integrated horizontal mass flux to estimate NH_3 flux from a simulated feed yard situation, focusing on small 10-meter-wide circular plots.

2-A.3.4 (Relaxed) Eddy Accumulation

The eddy accumulation method estimates the vertical flux of gas using two canisters for up- and downdrafts. The relaxed eddy accumulation method builds on this, but the sample is collected at a constant volume rate rather than with proportional sampling. This method does not need fast-response sensors for either rate, unlike eddy covariance (AMS, 2012; Hicks and Baldocchi, 2020). On the other hand, it is more labor-intensive than methods like eddy covariance (Nelson et al., 2017). It has been used to measure NH_3 fluxes (due to fertilizer application) over a corn canopy (Nelson et al., 2017). Parameters include (Harper et al., 2011; Nelson et al., 2017):

- Wind speed and direction
- Temperature sensor
- Gas concentration of both updrafts and downdrafts (two canisters)

2-A.4 Data Sources and Tools

Below are brief descriptions of known data sources and tools (hybrid methods), which may be used in conjunction with the methods described above.

2-A.4.1 Operation Tillage Information System (OpTIS)

OpTIS uses satellite-based remote sensing data to monitor conservation practices using maps of tillage, residue cover, winter cover, and soil health practices (CTIC, 2022). The system uses farm-field-scale data to perform calculations. OpTIS data are available for 2005 through 2019 for the U.S. Corn Belt, an area that—as of December 2021—includes Illinois, Indiana, and Iowa, as well as parts

[2] FLUXNET is a network of regional eddy covariance measurements to aid data exchange (U.S. DOE, 2021).

of Kansas, Kentucky, Michigan, Minnesota, Montana, Nebraska, Ohio, Oklahoma, South Dakota, Tennessee, and Wisconsin.

2-A.4.2 Landsat

Landsat is a series of U.S. satellites that collect Earth observations, which can be used to detect and measure land cover/land-use change, evaluate the health of ecosystems, and determine water availability (NASA, 2022). The most recent Landsat was equipped with sensors in the visible, near-infrared, short wave, and thermal infrared to collect moderate-resolution measurements of Earth (Roy et al., 2014; NASA, 2022).

The remote sensing data collected from Landsat can be used in agriculture and forestry applications. Landsat data were used to compare high-resolution maps of forest cover from 2000 to 2012 to understand how forests have changed on a global scale, allowing the study to be spatially explicit and determine annual trends in gross forest losses and gains (Hansen et al., 2013). Imagery from Landsat has been used since 1972 to monitor croplands. Field conditions can be identified using zone-mapping to aid in field-level management and increase crop yields (Leslie et al., 2017).

2-A.4.3 Sentinel Data

The European Space Agency's Earth observation program, Copernicus, has a series of satellite missions called Sentinels for land, ocean, and atmospheric monitoring. The TROPOspheric Monitoring Instrument (TROPOMI) is an imaging spectrometer that monitors greenhouse gases aboard the Sentinel-5P (ESA, 2022a). Sentinel-1 can classify forest types, map forest fire scars, and estimate biomass for forest applications, as well as monitor croplands, crop conditions, and soil degradation for agricultural applications (ESA, 2022b).

2-A.4.4 Planet Data

Planet is a privately owned company that provides daily satellite RGB (red-green-blue) composite images and near infrared images to customers for applications in defense, agriculture, and forestry. Planet has deployed a series of nanosatellites called constellations to allow for expansive coverage of Earth for daily image delivery (Planet Labs, 2022). Planet images combined with airborne LiDAR measurements have been used to develop a map of the aboveground tropical forest carbon stocks and emissions of Peru (Csillik et al., 2019).

Chapter 3 Quantifying Greenhouse Gas Sources and Sinks in Cropland and Grazing Land Systems

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Acronyms, Chemical Formulae, and Units

C	carbon
$CaCO_3$	limestone
CEAP	Conservation Effects Assessment Project
CH_4	methane
cm	centimeter
CO	carbon monoxide
CO_2	carbon dioxide
CO_2-eq	carbon dioxide equivalents
dbh	diameter at breast height
EC	eddy covariance
ESD	Ecological Site Description
GHG	greenhouse gas
GHGI	GHG emissions intensity
H_2CO_3	carbonic acid
ha	hectare
HCO_{3-}	bicarbonate
HNO_3	nitric acid
IPCC	Intergovernmental Panel on Climate Change
K	potassium
kg	kilogram
m	meter
Mg	megagram
$MgCa(CO_3)_2$	dolomite
N	nitrogen
N_2O	nitrous oxide
NH_3	ammonia
NH_4+	ammonium
NO_3-	nitrate
NO_x	nitrogen oxides
NPP	net primary production
NRCS	Natural Resources Conservation Service
NUE	nitrogen use efficiency
Pg	petagram
PRISM	Parameter-Elevation Regressions on Independent Slopes Model
PRP	pasture/range/paddock
RMSE	root mean square error
S	sulfur
SOC	soil organic carbon
SSURGO	Soil Survey Geographic Database
spg	specific gravity of wood on a green volume to dry-weight basis.
SWAT	Soil and Water Assessment Tool
USDA	U.S. Department of Agriculture
U.S. EPA	U.S. Environmental Protection Agency

3. Quantifying Greenhouse Gas Sources and Sinks in Cropland and Grazing Land Systems

This chapter provides methodologies and guidance for reporting greenhouse gas (GHG) emissions and sinks at the entity scale for cropland and grazing land systems:

- Section 3.1 provides an overview of cropland and grazing land systems management practices and their resulting GHG emissions, system boundaries and temporal scale, a summary of the selected methods, data requirements and sources, and estimating GHG emissions.
- Section 3.2 provides the estimation methods. A single method is provided for each of the GHG emission sources (and sinks), based on the best available method for application in an operational system for entity-scale reporting. A single method was chosen to ensure consistency in emission estimation by all reporting entities.

Two appendixes accompany this chapter, summarized below:

- Appendix 3A provides the rationale and technical documentation for the methods as well as a discussion on GHG intensity calculations.
- Appendix 3B summarizes research gaps for estimating GHG emissions in cropland and grazing lands that could provide a basis for future development of the methods in this chapter.

Additional background information on the impact of cropland and grazing land management are available in the 2014 report.

3.1 Overview

Cropland and grazing land systems are managed in a variety of ways, which results in varying degrees of GHG emissions or sinks. Table 3-1 describes the sources of emissions or sinks and the section in which methodologies are provided, along with the corresponding GHGs.

This section provides guidance on reporting GHG emissions associated with entity-level fluxes from farm and ranch operations. The guidance focuses on methods for estimating the influence of land use and management practices on GHG emissions (and sinks) in crop and grazing land systems.

Table 3-1. Overview of Cropland and Grazing Land Systems Sources and Associated GHGs

Section	Source	Method for GHG Estimation			Description
		CO_2	N_2O	CH_4	
3.2.1; 3.2.2	Biomass and litter carbon stock changes	✓			Estimating herbaceous biomass carbon stock during changes in land use is necessary to account for the influence of herbaceous plants on carbon dioxide (CO_2) uptake from the atmosphere, storage in the terrestrial biosphere, and associated CO_2 uptake or loss with land use conversion. Agroforestry and perennial tree and other woody crop systems also have longer term gains or losses of carbon based on the management of trees in these systems.

Section	Source	Method for GHG Estimation			Description
		CO_2	N_2O	CH_4	
3.2.3	Soil organic carbon (SOC) stock changes for mineral soils	✓			SOC stocks are influenced by land use and management in cropland and grazing land systems, as well as conversion from other land uses into these systems (Ogle et al., 2019a). SOC pools can be modified due to changes in carbon inputs and outputs (Paustian et al., 2016).
3.2.3	SOC stock changes for organic soils	✓			Emissions occur in organic soils following drainage due to the conversion of an anaerobic environment with a high water table to aerobic conditions (Ogle et al., 2019a), resulting in a significant loss of carbon to the atmosphere (Ogle et al., 2003).
3.2.4	Direct and indirect nitrous oxide (N_2O) emissions from mineral soils		✓		N_2O is emitted from cropland both directly and indirectly (Hergoualc'h et al., 2019). Direct emissions are fluxes from cropland or grazing lands where there are nitrogen additions or nitrogen mineralized from soil organic matter. Indirect emissions occur when reactive nitrogen is volatilized as ammonia (NH_3) or nitrogen oxides (NO_x), or transported via surface runoff or leaching in soluble forms from cropland or grazing lands, leading to N_2O emissions in another location.
3.2.4	Direct N_2O emissions from drainage of organic soils		✓		Organic soils (i.e., *Histosols*) are a special case in which drainage leads to high rates of nitrogen mineralization and increased N_2O emissions. The method assumes that organic soils have a significant organic horizon in the soil, and so are significant inputs of nitrogen from the oxidation of organic matter.
3.2.5	Methane (CH_4) flux for nonflooded soils			✓	This method addresses the influence of cropland and grazing land management on CH_4 flux for nonflooded soils. Agronomic activity universally reduces CH_4 uptake in cropland soils (Mosier et al., 1991; Robertson et al., 2000; Smith et al., 2000) and may also limit CH_4 uptake in grazing land soils (McDaniel et al., 2019).
3.2.6	CH_4 emissions from rice cultivation			✓	Several management practices affect CH_4 emissions from rice systems. The method addresses key practices including the influence of water management, residue management, and organic amendments on CH_4 emissions from rice (Yan et al., 2005; Linquist et al., 2018).
3.2.7	CO_2 from liming	✓			The addition of lime to soils is typically thought to generate CO_2 emissions to the atmosphere (de Klein et al., 2006). However, prevailing conditions in U.S. agricultural lands lead to lower CO_2 emissions than expected because the majority of lime is dissolved in the presence of carbonic acid (H_2CO_3) (West and McBride, 2005).
3.2.8	Non-CO_2 emissions from biomass burning		✓	✓	Biomass burning leads to emissions of CO_2 as well as other GHGs or precursors to GHGs that are formed later through additional chemical reactions. Note: CO_2 emissions are addressed in the biomass C stock change estimation to ensure that there is no double counting.

Section	Source	Method for GHG Estimation			Description
		CO_2	N_2O	CH_4	
3.2.9	CO_2 from urea fertilizer application	✓			Urea fertilizer application to soils contributes CO_2 emissions to the atmosphere (de Klein et al., 2006). CO_2 is incorporated into the urea during the manufacturing process: in the United States, the source of the CO_2 is the fossil fuel used for NH_3 production. The CO_2 captured during NH_3 production is released following application to soils, and as such is included in the farm-scale entity reporting.

3.1.1 Description of Sector

Croplands include all systems used to produce food, feed, and fiber, in addition to feedstocks for bioenergy production. Croplands are used to produce crops—both cultivated and noncultivated—for harvest (U.S. EPA, 2020). Cultivated crops are typically categorized as row or close-grown crops, such as corn, soybeans, wheat, and vegetables. Noncultivated crops (or those occasionally cultivated to replenish the crop) include hay, perennial crops (e.g., orchards and vineyards), and horticultural crops. The majority of cropland in the United States is in upland systems outside wetlands (as defined in section 6.1.1), and these systems may or may not be irrigated. Rice can be grown on natural or constructed wetlands; this chapter refers to both systems as flooded rice. Wetlands can also be drained for crop production—in which case they are considered croplands because their principal use is crop production. Croplands also include agroforestry systems that are a mixture of crops and trees, such as alley cropping, shelterbelts, and riparian buffers. Some croplands may be set aside from production and considered reserve cropland.

Grazing lands are systems that are used for livestock production and include rangelands and pasturelands. Rangeland is a land cover or use composed of grasses, grass-like plants, forbs, shrubs, and trees that is typically unsuited to cultivation because of physical limitations such as low and erratic precipitation, rough topography, poor drainage, or cold temperatures. Rangeland can include the following: (i) natural lands that have not been cultivated and consist of a historic complement of adapted plant species; and (ii) natural (go-back lands, old-field) or converted revegetated lands that are managed like native vegetation. Pastureland is a land use in which introduced or domesticated (tame) and/or native forage species mixtures are established through seeding, sprigging, and other practices that can be grazed and/or occasionally hayed or deferred for environmental purposes. Various degrees of management inputs may be applied, such as fertilization, liming, overseeding with grasses and legumes, mowing, remedial tillage, and irrigation (USDA, 2022). Note that for purposes of applying methods in this guidance, land that meets the definition of forest land is considered forest land regardless of other management such as grazing, and areas primarily used for crop or hay production are considered croplands.

3.1.2 Resulting GHG Emissions

Cropland and grazing lands can be sources of CO_2, N_2O, and CH_4 emissions and have the potential to sequester carbon with changes in management (Smith et al., 2008; Paustian et al., 2016). Moreover, N_2O emissions from the management of agricultural soils are a key source of GHG emissions in the United States (U.S. EPA, 2020). N_2O emissions result from the processes of nitrification and denitrification, which are influenced by land use and management activity, especially synthetic fertilizer management. Land use and management can also influence carbon stocks in biomass, dead biomass, and soil pools. Carbon stocks can be enhanced or reduced depending on land use and management practices (CAST, 2004; Paustian et al., 2016; Smith et al., 2008). For example, burning biomass can initially reduce biomass carbon stocks, but can also provide stimulus to enhance plant production and ecosystem carbon storage, particularly in grazing land systems. In addition, combustion of biomass will lead to non-CO_2 GHG emissions—CH_4, N_2O, and emissions of other aerosol gases (carbon monoxide [CO], NO_x)—that can be later converted to GHGs in the atmosphere or once deposited onto soil.

While the greatest source of methane is enteric fermentation and waste management in livestock production, soils in crop and grazing land systems can also be a source or sink for CH_4 depending on the conditions and management of soil. Methane can be removed from the atmosphere through the process of methanotrophy in soils. Methanotrophy occurs under aerobic conditions and is common in most soils that do not have standing water. In contrast, CH_4 is produced in soils through the process of methanogenesis, which occurs under anaerobic conditions, particularly soils with standing water such as flooded rice production. Both processes are driven by the activity of microorganisms in soils, and their rate of activity is influenced by land use and management.

3.1.3 Management Interactions

The influence of crop and grazing land management on GHG emissions is not typically the simple sum of each practice's effect. The influence of one practice can depend on another practice. For example, the influence of tillage on soil carbon will depend on residue management. The influence of nitrogen fertilization rates on N_2O emissions can depend on the type of fertilizer. Because of these synergies, estimating GHG emissions from crop and grazing land systems will depend on a complete description of the practices used in the operation, including past management to capture legacy effects on GHG emissions.

3.1.4 Mitigation

Crop and grazing land management influence GHG emissions. These can be reduced through practices that reduce N_2O emissions that would have otherwise occurred, reduce CH_4 emissions, or enhance biomass or soil carbon stocks (CAST, 2004, 2011; Paustian et al., 2016; Smith et al., 2008; Robertson et al. 2022). Operators of cropland systems use a variety of practices that have implications for emissions, such as nutrient additions, irrigation, liming applications, organic amendments such as manure and biochar, tillage practices, residue management, fallowing fields, forage, and crop selection (including harvested and cover crops), setting aside lands from production, erosion control practices, water table management in wetlands, and drainage of wetlands. Operators of grazing systems also have a variety of management options that influence GHG emissions, such as stocking rate, forage selection, use of prescribed fires, nutrient applications, wetland drainage, irrigation, liming applications, and silvopastoral practices.

The influence of these practices partly depends on past management, as well as the direct influence of these management activities on processes driving GHG emissions, biomass, and soil carbon stock changes. Some practices will almost always reduce GHG emissions, such as reducing mineral nitrogen fertilization rates (Bouwman et al., 2002a, 2002b; Hergoualc'h et al., 2019), although reduced mineral fertilization may be offset with additional input of organic manures that limits the reduction in emissions. In addition, other practices can have contrasting influences on individual GHGs. For example, no-till can increase soil carbon depending on the climate and soil type (Ogle et al., 2019c), but may also increase N_2O emissions (van Kessel et al., 2012). Similarly, a midseason drain event with flooded rice production can decrease CH_4 emissions, but also leads to more N_2O emissions (Linquist et al., 2018).

Recognizing the complexities associated with management, the net impact of management changes on emissions can be estimated and the amount of mitigation quantified using the methods in section 3.2.

3.1.5 System Boundaries and Temporal Scale

System boundaries are defined by the coverage, extent, and resolution of the estimation methods. The coverage of methods in this chapter can be used to estimate GHG emission sources from farm and ranch operations, including emissions associated with biomass carbon, litter carbon, and soil carbon stock changes; CH_4 and N_2O fluxes from soils; emissions from burning of biomass; and CO_2 fluxes associated with urea fertilization and addition of carbonate limes.

GHG emissions also occur with the production of management inputs, such as synthetic fertilizers and pesticides, and the processing of food, feed, fiber, and bioenergy feedstock products following harvest, but methods are not provided to estimate these emissions. Emissions from energy use, including those occurring on the entity's operation, are also not addressed.

The methods provided for crop and grazing land systems have a resolution of an individual parcel of land or field and include the spatial extent of all land parcels in an entity's operation. Land parcels are areas with uniform management that are used to produce a single crop or rotation of crops, or to raise livestock (i.e., pasture, rangeland). Emissions are estimated for each individual parcel that is used for cropland and grazing land on the operation, and then the emissions are added together to estimate the total emissions from the crop and grazing land systems in the entity's operation. The totals are then combined with emissions from forests and livestock to determine the overall emissions from the operation based on the methods provided in other chapters in this guidance. Emissions are estimated on an annual basis for as many years as needed for GHG emissions reporting. See chapter 2 as needed for additional details on accounting boundaries.

3.1.6 Summary of Selected Methods

This chapter describes methods for estimating biomass and soil carbon stock changes, soil N_2O emissions, CH_4 flux for nonflooded soils, CH_4 emissions from flooded rice, CO_2 emissions from liming, biomass burning non-CO_2 GHG emissions, and CO_2 emissions from urea fertilizer application (see table 3-2). The methods are classified according to the system of methodological tiers developed by the Intergovernmental Panel on Climate Change, or IPCC (2019), which is based on the complexity of different approaches for estimating GHG emissions. See chapter 1 for more information.

The methods provided in this chapter range from the simple Tier 1 approaches to the most complex Tier 3 approaches. Higher tier methods, particularly Tier 3 methods, are expected to reduce uncertainties in the emission estimates if sufficient activity data are available and the methods are well developed and calibrated as demonstrated with adequate testing (Ogle et al., 2019a).

Table 3-2. Overview of Sources and Selected GHG Estimation Methods for Cropland and Grazing Land Systems

Section	Source	Method
3.2.1	Biomass carbon stock changes	Herbaceous biomass is estimated with an IPCC Tier 2 method using entity-specific data as input into the IPCC equations (Ogle et al., 2019b; McConkey et al., 2019). Woody plant growth and losses in agroforestry or perennial tree crops are estimated with an IPCC Tier 3 method, using a measurement-based approach with entity input. Other woody perennial crops are estimated with the IPCC Tier 1 method (Ogle et al., 2019b).
3.2.3	SOC stocks for mineral soils	An IPCC Tier 3 method is used to estimate the SOC stock changes to a 30 cm depth for most crops and mineral soils using the DayCent process-based model (See U.S. EPA, 2020 for information about the Tier 3 model). SOC stock changes for other crops and mineral soil types are estimated with an IPCC Tier 2 method to a 30 cm depth (Ogle et al., 2003). Biochar soil amendments impacts on SOC are estimated with a Tier 2 method (Ogle et al., 2019a; Woolf et al., 2021).
3.2.3	SOC stocks for organic soils	Carbon dioxide emissions from the drainage of organic soils (i.e., *Histosols*) are estimated with an IPCC Tier 2 method for the entire soil profile (Ogle et al., 2003).
3.2.4	Direct N_2O emissions from mineral soils	The direct N_2O emissions are estimated with an IPCC Tier 3 method using the DayCent process-based model for most crops and grazing lands (U.S. EPA, 2020). Other crops are estimated with an adapted IPCC Tier 1 method (Hergoualc'h et al., 2019) that includes some scaling of emissions for select practices, including nitrification inhibitors, biochar or slow-release fertilizers, and no-till adoption.
	Direct N_2O emissions from drainage of organic soils	Direct N_2O emissions from the drainage of organic soils, i.e., *Histosols*, are estimated with the IPCC Tier 1 method (Drösler et al., 2013).
	Indirect N_2O emissions	Indirect soil N_2O emissions are estimated with the IPCC Tier 1 method (Hergoualc'h et al., 2019).
3.2.5	CH_4 flux for nonflooded soils	The CH_4 flux for nonflooded mineral soil is estimated based on the average values for CH_4 uptake in natural vegetation—whether grassland or forest—attenuated by current cropland and grazing land practices. This approach is an IPCC Tier 3 method. The CH_4 flux for drained organic soils, i.e., *Histosols*, is estimated with a Tier 1 method (Drösler et al., 2013)
3.2.6	CH_4 emissions from flooded rice cultivation	CH_4 emissions from the largest rice-producing regions in the United States, the Mid-South and California, are estimated with an IPCC Tier 2 method using emission factors that are specific to these regions (Linquist et al., 2018). The remainder of rice production areas are estimated with the IPCC Tier 1 method (Ogle et al., 2019b).
3.2.7	CO_2 from liming	An IPCC Tier 2 method is used to estimate CO_2 emissions from the application of carbonate limes (de Klein et al., 2006) with emission factors specific to conditions in the United States (adapted from West and McBride, 2005).
3.2.8	Non-CO_2 emissions from biomass burning	Non-CO_2 GHG emissions from biomass burning of grazing land vegetation or crop residues are estimated with the IPCC Tier 1 method (Aalde et al., 2006).
3.2.9	CO_2 from urea fertilizer application	CO_2 emissions from the application of urea or urea-based fertilizers to soils are estimated with the IPCC Tier 1 method (de Klein et al., 2006).

Tier 1 methods are used for estimating biomass carbon stock changes for herbaceous and nontree woody plants (i.e., shrubs and vines), CO_2 emissions from urea fertilization, CH_4 emissions from some regions with flooded rice and drained organic soils, direct soil N_2O emissions for some crops and soils, indirect soil N_2O emissions, direct soil N_2O emissions from drained organic soils, and biomass burning non-CO_2 GHG emissions. These methods are the most generalized globally and cannot capture specific conditions at local sites, and consequently have more uncertainty for estimating emissions from an entity's operation.

Direct soil N_2O emissions for most crops and mineral soils, CH_4 emissions from rice production in the Mid-South and California, CO_2 emissions from liming, SOC stock changes for some crops and mineral soil types, and soil carbon stock changes for drained organic soils all have elements of Tier 2 methods but may rely partly on emission factors provided by IPCC. These methods incorporate information about conditions specific to U.S. agricultural systems and the influence on emission rates, but again lack specificity for local site conditions in many cases.

Soil carbon stock changes and direct soil N_2O emissions for most crops and mineral soils are estimated using a Tier 3 method with a process-based simulation model (i.e., DayCent). Methane flux for nonflooded mineral soils is also estimated with a Tier 3 method, due to the absence of IPCC guidance for estimating land use and management effects on CH_4 flux associated with nonflooded mineral soils. A Tier 3 method with a measurement-based approach is used to estimate woody biomass carbon stock changes for agroforestry and woody perennial tree crops.

The Tier 3 methods, particularly the process-based model and measurement-based approaches, have the greatest potential for accurate estimation of the influence of local conditions on GHG emissions. The models underlying these methods have a general set of parameters that have been calibrated across a national dataset. The DayCent model approach also incorporates drivers associated with local conditions, including specific management practices, soil characteristics, and weather patterns, providing estimates of GHG emissions that are more specific to an entity's operation. The measurement-based approach for agroforestry and woody perennial tree crops incorporates local measurements from the entity's land parcels to develop stock changes more specific to the operation. Future research and refinements of the cropland and grazing land methods will likely incorporate more Tier 3 methods, and thus provide a more accurate estimation of GHG emissions based on local conditions for entity reporting.

All methods include a range of data sources from varying levels of specificity on operation-specific data to national datasets. An entity will need to collect operation-specific data: general activity data related to farm and livestock management practices (e.g., tillage practices, grazing practices, fertilizer use). National datasets are recommended for ancillary data requirements in the methods, such as climate data and soil characteristics.

3.2 Estimation Methods

This section provides methods for estimating GHG emissions from cropland and grazing land systems—specifically, for estimating emissions for a given year on a parcel of land. A parcel is a field in an operation with uniform management. (If management varies across the field, then the field should be subdivided into separate parcels for estimating emissions.) The methods are applied for both croplands that remain croplands and grazing lands that remain grazing lands (as categorized by IPCC), as well as land that has been converted to croplands or grazing lands.

Trends across years or comparisons to baselines can be made using annual emission estimates. This chapter does not give guidance on how to develop baselines or project trends for emission estimation. Emissions from carbon stocks are based on estimating the change in stock from the beginning to the end of the year, emissions of N_2O and CH_4 are based on estimating total annual emissions. Methods are also provided for estimating total emissions of GHG precursor gases during biomass burning, as well as nitrogen compounds that are volatilized or subject to leaching and runoff from cropland or grazing land and that are later converted into GHGs.

GHG emission methods range in complexity for the different source categories according to the state of the science and prior method development. Simple methods were chosen for several of the emission or carbon stock change source categories, given the current state of methods development for these categories. Although simplicity may be preferred for transparency in estimation, some of the methods use more complex approaches, such as process-based simulation models, because they greatly improve accuracy and incorporate more information about local conditions that influence emissions.

3.2.1 Biomass Carbon Stock Changes

Box 3-1. Method for Estimating Biomass Carbon Stock Changes[1]

Herbaceous

- The method consists of estimating the annual biomass stock for cropland or grazing land following a land-use change to cropland and grazing land. This method only addresses a change in the herbaceous biomass carbon stocks in the year following a land-use change, consistent with the IPCC methods (McConkey et al., 2019; Ogle et al., 2019b).

Woody

- The method consists of estimating biomass stock from trees in croplands and grazing lands using allometric equations and entity-measured data (Chojnacky et al., 2014) for all years. The data collection method depends on whether the woody plants are regularly or randomly spaced.
- For parcels with shrubs, use the IPCC default for hedgerows to estimate biomass carbon stock from shrubs (Ogle et al., 2019b). For vineyards, use the IPCC default for vine crops to estimate biomass carbon stock.

3.2.1.1 Description of Method

A modified version of the methodology developed by IPCC (McConkey et al., 2019; Ogle et al., 2019b) has been adopted for entity-scale reporting in the United States for herbaceous and woody biomass stock changes associated with land-use change (see appendix 3A.1 for the rationale). This method can be used for annual crops, set-aside cropland, grazing lands, orchards, vineyards, and agroforestry systems (e.g., windbreaks, alley cropping, silvopasture, riparian forest buffers). Forest farming (also referred to as multistory cropping) is addressed with the methods and approaches presented in chapter 5.

To determine the change in biomass carbon stocks, subtract the total biomass carbon stock in the previous year from the total stock in the current year, which will include both herbaceous and woody biomass. The herbaceous stock changes are only estimated in a year with a land-use change

[1] Biomass C stock changes are only estimated for herbaceous biomass in the year following a land-use change but are estimated for woody biomass in all years regardless of if the land has recently been converted from another land use or not recently converted from another land use.

on the land parcel including *Land Converted to Cropland* and *Land Converted to Grazing Land.*[2] In contrast, the change in woody biomass associated with shrub biomass or vineyards is estimated using a gain-loss method for all years. Use equation 3-1 to estimate the *total biomass carbon stock change* for a land parcel over a year. For woody biomass, the stocks may not be estimated in consecutive years[3] so the stock change will need to be divided by the number of years between the estimates.

Equation 3-1: Total Biomass Carbon Stock Change

$$\Delta C_{biomass} = (\Delta C_{HB} + \Delta C_{WB}) \times \mathrm{CO_2MW}$$

Where:

$\Delta C_{biomass}$	=	total annual change in biomass carbon stock (metric tons CO_2-eq)
ΔCHB	=	total annual change in herbaceous biomass carbon stock (metric tons C), set to 0 if there is no land-use change
ΔCWB	=	total annual change in woody biomass carbon stock (metric tons C)
CO_2MW	=	ratio of molecular weight of CO_2 to carbon = 44/12

$$\Delta C_{HB} = H_t - H_{t-1}$$

Where:

ΔC_{HB}	=	total annual change in herbaceous biomass carbon stock (metric tons C), set to 0 if there is no land-use change
H	=	herbaceous biomass stock (metric tons C)
t	=	current year stock following the land-use change
$t-1$	=	previous year's stock prior to the land-use change

$$\Delta C_{WB} = (W_t - W_{t-1}) + OWP$$

Where:

ΔC_{WB}	=	total annual change in woody biomass carbon stock (metric tons C)
W	=	annual woody tree biomass stock (metric tons C)
OWP	=	annual change in other woody plant biomass stock (shrubs and vines) (metric tons C)
t	=	current year stock
$t-1$	=	previous year's stock

The estimation method for herbaceous and woody biomass stocks in cropland and grazing land is given below. If the previous land use is forest land, estimate the carbon stocks using methods found in chapter 5.

Herbaceous Biomass

Use equation 3-2 to estimate the annual herbaceous biomass carbon stock in a land parcel for cropland or grazing land following a land-use change during the year.

[2] See chapter 7 for information about land-use change.

[3] Woody plants may be sampled every 5 years or another time interval that is not in consecutive years.

Equation 3-2: Mean Annual Herbaceous Biomass Carbon

$$H = [H_{peak} + (H_{peak} \times R)] \times A \times Y_f$$

Where:

H	=	annual herbaceous biomass carbon stock (metric tons C)
H_{peak}	=	annual peak aboveground biomass (metric tons C/ha)
R	=	root-to-shoot ratio (unitless)
A	=	area of land parcel (ha)
Y_f	=	approximate fraction of calendar year representing the growing season (unitless)

The annual biomass stock is intended to represent the average amount of C in the biomass in the annual cycle and is calculated by the peak annual biomass (weighted by fraction of year in growing season) and zero biomass for the non-growing season when no crop exists and both litter and roots are decomposing relatively quickly (Gill et al., 2002).

Use equation 3-3 to estimate the peak aboveground herbaceous biomass in a land parcel from harvest yield data in croplands or peak forage yields in grazing lands.

Equation 3-3: Peak Aboveground Herbaceous Biomass Carbon

$$H_{peak} = (Y \div HI) \times DM \times F_C$$

Where:

H_{peak}	=	annual peak aboveground herbaceous biomass carbon stock (metric tons C/ha)
Y	=	fresh weight of the annual crop harvest or forage yield (metric tons yield/ha)
HI	=	harvest index (metric tons yield/metric tons biomass)
DM	=	dry matter content of harvested crop biomass or forage (metric tons dry matter/metric tons biomass)
F_C	=	carbon fraction of aboveground biomass (metric tons C/metric tons dry matter)

Equation 3-3 captures the influence of land-use change on biomass carbon stocks and is based on the crop or forage grown on the land parcel in the year of the land-use change, or the next year if no crop or forage is planted during the year of the conversion. For grazing lands, the HI is set to 1. See other land use chapters for methods to estimate herbaceous biomass C stock if the previous land use is not cropland or grazing land.

The entity may not harvest a crop following a land-use change due to drought, pest outbreaks, or other crop failures. In those cases, the entity may use the average yield that they have harvested in the past for the crop on the land parcel. Alternatively, the entity may use average county yields from the USDA, National Agricultural Statistics Service[4] (NASS) for the crop.

[4] https://quickstats.nass.usda.gov/

The dry matter content, harvest index, and root-to-shoot ratios are provided in table 3-3. The carbon fraction for herbaceous biomass is provided in table 3-4.

Table 3-3. Dry Matter Content of Harvested Crop Biomass, Harvest Index, and Root-to-Shoot Ratios for Various Crops With 95-Percent Confidence Intervals in Parentheses

Crop	Dry Matter Content (metric tons dry matter/metric tons biomass)	Harvest Index (metric tons yield/metric tons biomass)	Root-to-Shoot Ratio
Food Crops			
Barley	0.865 (±0.033)	0.46 (±0.086)	0.11 (±0.100)
Beans	0.84 (±0.028)	0.46 (±0.086)	0.08 (±0.072)
Corn grain	0.86 (±0.016)	0.53 (±0.080)	0.18 (±0.175)
Corn silage	0.74 (±0.014)	0.95 (±0.314)	0.18 (±0.175)
Cotton	0.92 (±0.013)	0.40 (±0.080)	0.17 (±0.075)
Millet	0.90 (±0.017)	0.46 (±0.081)	0.25 (±0.228)
Oats	0.865 (±0.016)	0.52 (±0.097)	0.40 (±0.364)
Peanuts	0.91 (±0.017)	0.40 (±0.066)	0.07 (±0.009)
Potatoes	0.20 (±0.019)	0.50 (±0.100)	0.07 (±0.031)
Rice	0.91 (±0.015)	0.42 (±0.118)	0.22 (±0.029)
Rye	0.90 (±0.017)	0.50 (±0.094)	0.14 (±0.126)
Sorghum grain	0.86 (±0.016)	0.44 (±0.065)	0.18 (±0.175)
Sorghum silage	0.74 (±0.014)	0.95 (±0.314)	0.18(±0.175)
Soybean	0.875 (±0.015)	0.42 (±0.070)	0.19 (±0.171)
Sugarbeets	0.15 (±0.002)	0.40 (±0.096)	0.43 (±0.189)
Sugarcane	0.258 (±0.003)	0.75 (±0.480)	0.18 (±0.067)
Sunflower	0.91 (±0.017)	0.27 (±0.030)	0.06 (±0.026)
Tobacco	0.80 (±0.015)	0.60 (±0.198)	0.80 (±0.352)
Wheat	0.865 (±0.033)	0.39 (±0.069)	0.20 (±0.172)
Forage and Fodder Crops			
Alfalfa hay	0.87 (±0.016)	0.95 (±0.031)	0.87 (±0.190)
Nonlegume hay	0.87 (±0.016)	0.95 (±0.031)	0.87 (±0.190)
Nitrogen-fixing forages	0.35 (±0.12)	0.95 (±0.031)	1.1 (±0.233)
Nonnitrogen-fixing forages	0.35 (±0.012)	0.95 (±0.031)	1.5 (±0.318)
Perennial grasses	0.35 (±0.012)	0.95 (±0.031)	1.5 (±0.318)
Grass-clover mixtures	0.35 (±0.012)	0.95 (±0.031)	1.5 (±0.318)

Source: Revised from West et al., 2010.

Probability density functions have a normal distribution that can be used to propagate errors through the analysis and quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

Table 3-4. Carbon Fraction for Herbaceous Biomass With 95-Percent Confidence Interval

	FC	95-Percent Confidence Interval
Herbaceous biomass carbon fraction	0.45	0.42–0.47

Source: Expert judgement of authors.

Probability density functions have a normal distribution. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

Woody Tree Biomass

The following section provides general guidance for obtaining estimates of woody biomass carbon stocks on croplands and grazing lands using a measurement-based approach. This guidance is intended to provide the basic information needed to characterize a range of vegetation conditions from single rows of trees or shrubs, to natural stands of trees dispersed randomly. This method can be used for orchards, vineyards, and agroforestry systems.

The most precise way to characterize a population (e.g., all trees or shrubs on the entity's land) is to measure each individual tree in the population. This approach—typically described as a census—is the preferred method for collecting data on trees within the land parcel if feasible. If a parcel's size or the number of trees in it makes a census infeasible, sampling individuals from the population is acceptable for reporting biomass carbon stock changes. More information about sampling is provided in section 3.2.1.2. Trees are large woody perennial plants, capable of reaching at least 15 feet (4.6 meters) in height, with a diameter at breast height (dbh) or at root collar (if multi-stemmed woodland species) greater than 1 inch (2.5 centimeters). Woody plants that do not meet this definition may be considered shrubs.

After collecting the activity data for trees, i.e., diameter at breast height (dbh) as described in section 3.2.1.2, estimate the total change in woody biomass for a land parcel using equation 3-4.

Equation 3-4: Total Woody Tree Biomass Carbon Stock

$$W = \exp\left[ln(biomass_{abvg}) + biomass_{blwg}\right] \times M \times F_C$$

Where:

W	=	annual woody tree biomass stock (metric tons C)
$biomass_{abvg}$	=	aboveground woody biomass stock for trees 2.5 cm and larger in dbh (kg biomass dry matter)
$biomass_{blwg}$	=	belowground woody biomass stock for trees 2.5 cm and larger in dbh (kg biomass dry matter)
M	=	conversion factor for converting kg to metric tons (0.001)
F_C	=	carbon fraction of tree biomass (metric tons C/metric tons dry matter)

The carbon fraction for woody tree biomass is provided in table 3-5.

Table 3-5. Carbon Fraction for Woody Tree Biomass With 95-Percent Confidence Interval

	F_C	95-Percent Confidence Interval
Tree biomass carbon fraction	0.47	0.44–0.49

Source: Aalde et al., 2006, i.e., IPCC Tier 1 factors.

Probability density functions have a normal distribution that can be used to propagate errors through the analysis and quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

The total aboveground biomass in the sampling plots is estimated using equation 3-5, with measured dbh and species group for each tree stem within the plots. Equation parameters are chosen based on 35 species groups in the United States (Chojnacky et al., 2014; see table 3-6 below). Refer to table 3A-1. in appendix 3A.1 to determine which of 129 tree species are associated with the 35 species groups. For deciduous tree species not found in the list (e.g., fruit and nut species in orchards or agroforestry systems), use equation parameters associated with the hardwood group (Cornaceae/Ericaceae/Lauraceae/Platanaceae/Rosaceae/Ulmaceae).

Equation 3-5: Aboveground Woody Tree Biomass Stock

$$\ln\left(biomass_{abvg}\right) = \frac{\sum_{Plots}\sum_{Stems}\beta_0 + [\beta_1 \times \ln(dbh)]}{Plot_n} \times E_f \times A_T$$

Where:

$biomass_{abvg}$ = total aboveground woody biomass stock for trees 2.5 cm and larger in dbh for all plots in the land parcel (kg biomass dry matter)

β_0 and β_1 = model parameters for each stem (dimensionless: see table 3-6)

dbh = diameter at breast height for each stem (cm)

ln = natural log base "e" (2.718282)

$Plot_n$ = number of plots sampled

E_f = number of plots in a hectare (dimensionless)

A_T = area of land parcel with woody tree cover (ha)

The stems within a plot are summed to obtain a plot total; the plot totals are then summed to obtain the total aboveground woody biomass stock for all plots in the land parcel.

Table 3-6. Aboveground Biomass Model Parameters for 13 Conifer, 18 Hardwood, and 4 Woodland Taxa With 95-Percent Confidence Intervals[a]

Group	Taxon	β_0	95-Percent Confidence Interval	β_1	95-Percent Confidence Interval
Conifer	Abies, 0.35 spg[b]	−2.3123	±0.4625	2.3482	±0.4696
Conifer	Abies ≥ 0.35 spg	−3.1774	±0.6355	2.6426	±0.5285
Conifer	Cupressaceae, 0.30 spg	−1.9615	±0.3923	2.1063	±0.4213
Conifer	Cupressaceae, 0.30–0.39 spg	−2.7765	±0.5553	2.4195	±0.4839
Conifer	Cupressaceae, ≥ 0.40 spg	−2.6327	±0.5265	2.4757	±0.4951
Conifer	Larix	−2.3012	±0.4602	2.3853	±0.4771
Conifer	Picea, 0.35 spg	−3.0300	±0.6060	2.5567	±0.5113

Group	Taxon	β_0	95-Percent Confidence Interval	β_1	95-Percent Confidence Interval
Conifer	Picea, ≥ 0.35 spg	−2.1364	±0.4273	2.3233	±0.4647
Conifer	Pinus, 0.45 spg	−2.6177	±1.0471	2.4638	±0.9855
Conifer	Pinus, ≥ 0.45 spg	−3.0506	±1.2202	2.6465	±1.0586
Conifer	Pseudotsuga	−2.4623	±0.9849	2.4852	±0.9941
Conifer	Tsuga, 0.40 spg	−2.3480	±0.9392	2.3876	±0.9550
Conifer	Tsuga, ≥ 0.40 spg	−2.9208	±1.1683	2.5697	±1.0279
Hardwood	Aceraceae, 0.50 spg	−2.0470	±0.4094	2.3852	±0.4770
Hardwood	Aceraceae, ≥ 0.50 spg	−1.8011	±0.3602	2.3852	±0.4770
Hardwood	Betulaceae, 0.40 spg	−2.5932	±0.5186	2.5349	±0.5070
Hardwood	Betulaceae, 0.40–0.49 spg	−2.2271	±0.4454	2.4513	±0.4903
Hardwood	Betulaceae, 0.50–0.59 spg	−1.8096	±0.3619	2.3480	±0.4696
Hardwood	Betulaceae, ≥ 0.60 spg	−2.2652	±0.4530	2.5349	±0.5070
Hardwood	Cornaceae/Ericaceae/Lauraceae/ Platanaceae/Rosaceae/Ulmaceae	−2.2118	±0.4424	2.4133	±0.4827
Hardwood	Fabaceae/Juglandaceae, Carya	−2.5095	±0.5019	2.6175	±0.5235
Hardwood	Fabaceae/Juglandaceae, other	−2.5095	±0.5019	2.5437	±0.5087
Hardwood	Fagaceae, deciduous	−2.0705	±0.4141	2.4410	±0.4882
Hardwood	Fagaceae, evergreen	−2.2198	±0.4440	2.4410	±0.4882
Hardwood	Hamamelidaceae	−2.6390	±0.5278	2.5466	±0.5093
Hardwood	Hippocastanaceae/Tiliaceae	−2.4108	±0.4822	2.4177	±0.4835
Hardwood	Magnoliaceae	−2.5497	±0.5099	2.5011	±0.5002
Hardwood	Oleaceae, 0.55 spg	−2.0314	±0.4063	2.3524	±0.4705
Hardwood	Oleaceae, ≥ 0.55 spg	−1.8384	±0.3677	2.3524	±0.4705
Hardwood	Salicaceae, 0.35 spg	−2.6863	±0.5373	2.4561	±0.4912
Hardwood	Salicaceae, ≥ 0.35 spg	−2.4441	±0.4888	2.4561	±0.4912
Woodland[c]	Cupressaceae	−2.7096	±0.8129	2.1942	±0.6583
Woodland[c]	Fabaceae/Rosaceae	−2.9255	±2.0479	2.4109	±1.6876
Woodland[c]	Fagaceae	−3.0304	±1.2122	2.4982	±0.9993
Woodland[c]	Pinaceae	−3.2007	±0.3201	2.5339	±0.2534

Source: Chojnacky et al., 2014.

Probability density functions have a normal distribution that can be used to propagate errors through the analysis and quantify uncertainty. The method is based on available studies that provided pseudo-data from those empirical assessments to develop biomass estimates. The model was fit to the biomass estimates. Consequently, there may be additional uncertainty in the application of this method at the entity scale that is not quantified.

[a] Includes the relative uncertainty in estimates derived with equation 3-5, expressed conservatively on a percentage basis as half the 95-percent confidence interval based on pseudodata in Chojnacky et al. (2014). Estimates of woody tree biomass stocks by taxon that are calculated with equation 3-5 are assumed to have the uncertainty provided in this table, which can be used for error propagation.

[b] Where spg is the specific gravity of wood on a green volume to dry-weight basis.

[c] Woodland groups are based on diameter at root collar instead of dbh.

Use equation 3-6, in combination with equation parameters from table 3-7, to estimate the belowground biomass. Fine and coarse roots are treated separately in the calculation.

Equation 3-6: Belowground Woody Tree Biomass Stock

$$biomass_{blwg} = [CR \times biomass_{abwg}] + [FR \times biomass_{abwg}]$$

Where:

$biomass_{blwg}$ = belowground woody biomass stock for trees 2.5 cm and larger in dbh (kg biomass dry matter)

$biomass_{abvg}$ = aboveground woody biomass stock for trees 2.5 cm and larger in dbh (kg biomass dry matter)

CR = coarse root ratio

FR = fine root ratio

$$CR = \beta_0 + [\beta_1 \times \ln(dbh)]$$

$$FR = \beta_0 + [\beta_1 \times \ln(dbh)]$$

Where:

CR = coarse root ratio

FR = fine root ratio

dbh = diameter at breast height (cm)

ln = natural log base "e" (2.718282)

β_0 and β_1 = model parameters (dimensionless: see table 3-7)

Table 3-7. Belowground Biomass Model Parameters for Coarse and Fine Roots With 95-Percent Confidence Intervals[a]

Component	β_0	95-Percent Confidence Interval	β_1	95-Percent Confidence Interval
Coarse roots	−1.4485	±1.0864	−0.03476	±0.0261
Fine roots	−1.8629	±1.3972	−0.77534	±0.5815

Source: Chojnacky et al., 2014.

Probability density functions have a normal distribution that can be used to propagate error through the analysis and quantify uncertainty. The method is based on based on available studies that provided pseudo-data from those empirical assessments to develop biomass estimates.

[a] Given the limited pseudo-data used to develop the root-to-shoot ratio, a nominal uncertainty of ±75 percent is suggested and presented in the table based on Ogle et al. (2019b), which is expected to include the likely values at the entity scale.

Box 3-2. Projections of Woody Tree Biomass

For future estimation of carbon stocks, individual tree growth models such as those based on Lessard (2000) and Lessard et al. (2001) can be used in conjunction with the diameter-based allometric models (Chojnacky et al., 2014). Tree growth is dependent on many factors—and the longer the time estimate, the greater the uncertainty. Data from the U.S. Forest Service's Forest Inventory and Analysis program can be used to support growth increment models. Activity data include status (live or dead), which should be used in modeling future growth potential and carbon stock change.

Other Woody Biomass

Use equation 3-7 to estimate the total shrub and vine biomass carbon stock change for the land parcel. If stocks are not estimated for consecutive years, the stock change will need to be divided by the number of years between the estimates. The carbon accumulation factor for shrub and vine biomass is provided in table 3-8.

Equation 3-7: Other Woody Biomass Carbon Stock Change

$$OWP = (S_t - S_{t-1}) + (V_t - V_{t-1})$$

Where:

OWP	=	annual change in other woody plant biomass stock (shrubs and vines) (metric tons C)
S	=	woody biomass stock for shrubs (metric tons C)
V	=	woody biomass stock for vines (metric tons C)
t	=	current year stocks
t–1	=	previous year's stocks

$$S = \frac{\sum_{Plots}\sum_{\substack{Age\\Classes}}(N_s \times CA_s \times Y_s)}{Plot_n} \times E_f \times A_S$$

Where:

S	=	woody biomass stock for shrubs (metric tons C)
N_S	=	number of shrubs in sample plot (shrubs)
CA_S	=	carbon accumulation factor per shrub (metric tons C/shrub/year)
Y_S	=	age of shrubs up to 30 years of age (years); use 30 years if age is unknown, and assign an age of 30 to all shrubs older than that for estimating the stock
$Plot_n$	=	number of plots sampled
E_f	=	number of plots that fit into a hectare (dimensionless)
A_S	=	area of parcel with woody shrub cover (ha)

$$V = (A_v \times CA_v \times Y_v)$$

Where:

V	=	woody biomass stock for vines (metric tons C)
A_V	=	area of vines in the entire land parcel being estimated (ha)
CA_V	=	carbon accumulation factor for vineyards (metric tons C/ha/year)

Y_V	=	age of vines up to 20 years of age (years); use 20 years if age is unknown, and assign an age of 20 to all vines older than that for estimating the stock

Age classes for shrubs within a plot are summed to obtain plot totals, and then the plot totals are summed to obtain the total woody biomass stock for shrubs for all plots in the land parcel.

If there are shrubs in the land parcel, use IPCC Tier 1 hedgerow defaults for estimating carbon stock from shrubs (Ogle et al., 2019b). Specifically, use 0.00135 metric tons of carbon accumulation per shrub per year for up to 30 years to estimate total carbon stock for aboveground and belowground biomass. No additional increase in net growth is assumed after 30 years. If vineyards are part of the land parcel, use the IPCC Tier 1 default factor for vines (e.g., grapes) for estimating aboveground carbon stock for up to 20 years (Ogle et al., 2019b). No additional increase in net growth is assumed after 20 years.

Table 3-8. Carbon Accumulation Factors for Shrubs and Vines With 95-Percent Confidence Intervals

Component	Carbon Accumulation	95-Percent Confidence Interval
Shrubs	0.00135 metric tons C/shrub/year	±0.0007
Vines	0.28 metric tons C/ha/year	±0.07

Source: Ogle et al., 2019b, i.e., IPCC Tier 1 factors.

Probability density functions have a normal distribution that can be used to propagate error through the analysis and quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

If woody products are harvested from the system, estimate stock change using the approaches described in chapter 5. Woody products may be harvested from silvopasture, alley cropping, and other agroforestry practices, providing a variety of products such as veneer, saw timber, and bioenergy feedstocks.

Since this is a stock difference method, the entity should include any woody plant removals (trees, shrubs, and/or vines) that occurred in the current year to reflect the loss of carbon from the previous year. Carbon dioxide emissions associated with burning are not estimated. Non-CO_2 trace gas emissions occur from burning and can be estimated with methods described in section 3.2.8.

3.2.1.2 Activity Data

Herbaceous Biomass

Activity and related data needed to estimate biomass carbon for annual crops and grazing lands (as applicable) include:

- Crop type, cropland area, and harvest indices
- Type of forage, grazing area, and peak forage yield data
- Total aboveground yield of crop or peak forage yield for grazing lands (metric tons biomass per hectare)
- Root-to-shoot ratios
- Carbon fractions
- Dry matter content of forage and harvested crop biomass to estimate dry matter content

Peak forage estimates for grazing lands can be estimated using the biomass clipping method (see chapter 15 of USDA, 2011). This method requires removal of forage samples from the field. Other methods can also be used, including the comparative yield method for rangelands (see chapter 13 of USDA, 2011) or the Robel pole method on rangelands or pastures (Harmoney et al., 1997; Vermeire et al., 2002). Any sampling that is done, whether destructive or nondestructive, should occur at locations that are representative of the land parcel.

If sampling the forage is not feasible, default expected annual biomass production values are provided by the USDA Natural Resources Conservation Service (NRCS) in Ecological Site Descriptions (ESDs) (USDA, n.d.). After identifying the appropriate ESD, the entity would select the plant community that is representative of the parcel. These values represent total production for the site, so Y_f in equation 3-2 would be set to 1 if the aboveground forage production is obtained from an ESD.

Woody Biomass

To get activity data to estimate woody biomass carbon in croplands and grazing lands, an entity needs to conduct a basic inventory of woody species associated with the land parcel. Activity data (as applicable) include:

- Area of vegetation and/or linear distance of single rows of vegetation
- Species of trees, number by diameter class, and status (live or dead)
- Diameter at breast height for a sample of trees that capture the spacing arrangements and densities within the parcel
- Count, age, and status (live or dead) of shrubs that capture the spacing arrangements and densities within the parcel
- Area in vine crops for vineyards

If the entity does not know the age of the shrubs or vines, it should assume that the shrubs are beyond the 30-year threshold and the vines are beyond the 20-year threshold.

Box 3-3. Sampling Basics for Woody Plants in Croplands and Grazing Lands

For entities that use a sampling approach, there are many terms and definitions for sampling and estimation. This box describes a few important terms and concepts relevant to a basic land inventory—consistent with the methods described in this chapter, for which aboveground biomass carbon is the population parameter of interest. See McRoberts et al., 2015, for more details.

First is ***establishing a sampling frame*** for the trees within the population of interest. To do this, the population of trees must be identified on the land parcel. This can be accomplished with a paper map, a digital data product from web-based maps (e.g., Google, Bing), a product developed as part of a geographic information system, or information in another format. Once the location of trees is identified, a sample frame can be established that includes all possible sampling units (i.e., plots) within the land parcel. The selection of sample units is based on the sampling design within the sampling frame for the population.

- ***Equal probability sampling*** of the sampling units should be used: that is, sampling unit locations, i.e., trees, should have an equal probability of being selected for the sample within the land parcel. A convenient way to choose sample locations is systematic sampling—that is, overlaying a grid on the defined population.

- The ***plot configuration*** (the size and shape of the plot) may depend on the sampling method. For randomly spaced woody plants, it is recommended that the plot configuration use a fixed area with circular plots.
- Finally, it is important to determine an ***appropriate sample size***—the number of plots to be measured within the population. Typically, as the sample size increases, the variance of the population parameter of interest (e.g., woody biomass carbon stocks) decreases, and the precision of the estimate increases (McRoberts et al., 2015). To predict sample size, an entity must estimate a measure of variation and specify a maximum allowable error (Cochran, 1977). Interactive "sample size calculators" are available online.

Recommended inventory methods depend on whether the woody plants are organized in rows (single or multiple) such as windbreaks, orchards, or alley cropping or randomly spaced (e.g., riparian forest buffers, silvopasture systems converted from natural woodlands) (figure 3-1). If a parcel and/or the vegetation being surveyed is very homogenous and there is a complete census of the vegetation in the land parcel (species, age, and count), the entity will only need to sample a few individual trees to get an average dbh.

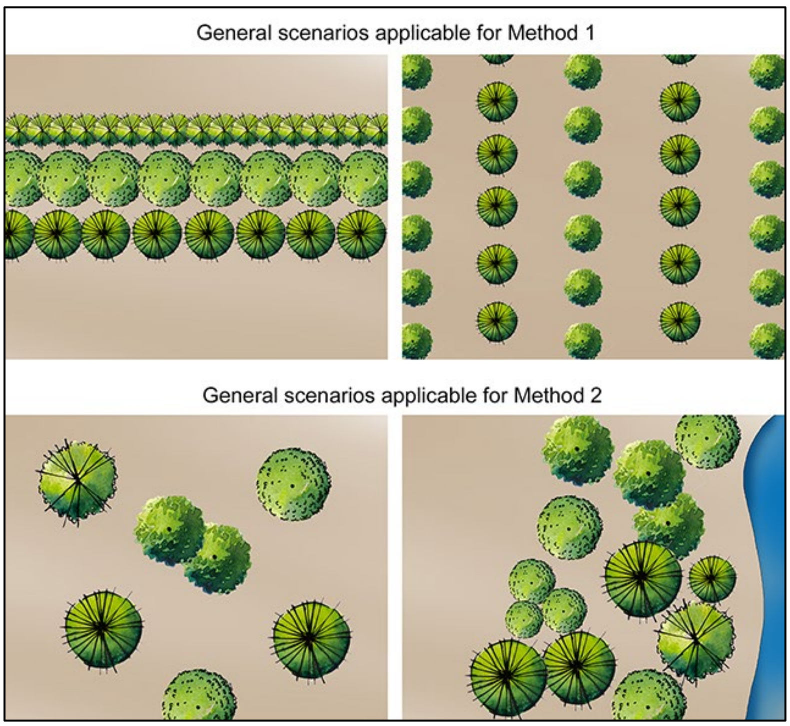


Figure 3-1. Plan Views Showing Which Method to Apply Based on Plant Arrangement

Method 1: In organized plantings, a sample plot with 10 consecutive trees or shrubs is recommended based on methods described in NRCS's *National Forestry Handbook* (USDA, 2004). Within a uniform parcel, a representative segment should be chosen within each row, assuming the same species are planted in the row. If the parcel is not uniform, additional sample plots of 10 plants may be necessary to capture differences. In future years, recording plot locations and measuring the same trees will reduce uncertainty. If a row has more than one tree species, sample only one species at a time, and treat each one as a separate row for length.

Record the species and status (alive or dead), along with measuring the dbh for trees. If the row contains shrubs, record the age and status. If the age is not known, assume shrubs are at the 15-

year midpoint on the 30-year maturity cycle. Measure and record the linear distance to the next tree or shrub in the row. Repeat until all 10 trees or shrubs have been inventoried. Record the total distance of the row that was sampled. Continue to the next row until all sampling is completed. Refer to available manuals for more guidance on sampling (USDA, 2004; Zobrist et al., 2012).

Method 2: In randomly spaced vegetation or where there are more than three to five rows, a standard fixed plot approach is recommended based on methods described in the *National Forest Handbook* (USDA, 2004). The standard fixed plot is a circle with a radius of 26.3 feet (8 meters), which represents a plot size of 1/20th or 0.05 acre (0.02 ha). Parcels of 1–10 acres (0.4–4.0 ha) require measurements from at least two fixed plots.

Take at least one extra fixed plot for each additional 10 acres of parcel size. If one portion of the stand has a different mix of species, was planted in a different year, or has a different soil or moisture regime resulting in different growing conditions, treat that area as a separate parcel in estimating carbon storage. Remember that increasing sample size reduces the variance of the population parameter of interest [e.g., woody biomass carbon stocks] and increases the precision of the estimate. Further, areas with substantial variability in the individuals within the population or the site conditions within the population may require additional sampling. To aid in remeasurement in future years, record plot locations.

Measure all trees with a stem height of 4.5 feet (1.37 meters) or more with a diameter greater than 1 inch (2.5 centimeters) that fall within a fixed plot. Measure the dbh and record the species and diameter of all trees inside that plot, including status (live or dead). For shrubs, record approximate age, status (live or dead), and number. Continue to the next plot until all sampling is completed. Refer to available manuals for more guidance on sampling (USDA, 2004; Zobrist et al., 2012).

3.2.1.3 Limitations and Uncertainty

Herbaceous biomass C: Use the explicit model-based method to estimate uncertainty for herbaceous biomass C (see chapter 8). Uncertainty is assumed to be minor for the management activity data provided by the entity, and therefore the values are assumed to be certain. The tables presented in section 3.2.1.1 provide the uncertainty for model parameters used in the equations for herbaceous biomass C, and these uncertainties are combined using a Monte Carlo simulation. See chapter 8 for more information about the explicit model-based method.

Specific sources of uncertainty are due to lack of precision in crop or forage yields, residue-yield ratios, root-to-shoot ratios, and carbon fractions, as well as the uncertainties associated with estimating the biomass carbon stocks for the other land uses. In particular, the herbaceous biomass method assumes that half of the crop harvest yields or peak forage amounts provide an accurate estimate of the mean annual carbon stock in cropland or grazing lands. This assumption warrants further study, and the method may be further refined in the future.

Woody biomass C: Use the measurement-based method to estimate uncertainty for the herbaceous biomass C (see chapter 8). Sampling and measurement error and error associated with regression models influence the uncertainty associated with estimating carbon in live trees (see Melson et al., 2011; further discussion in chapter 6). The tables in section 3.2.1.1 provide the uncertainty for the model parameters used in the equations for woody biomass C and the quantification of uncertainty in measurements are combined using a Monte Carlo simulation and discussed in the section 3.2.1.2. Uncertainties in measurements and model parameters are combined using a Monte Carlo simulation. See chapter 8 for more information about the explicit model-based method.

Estimating carbon in agroforestry trees, especially for young seedlings and saplings (up to about 10 years depending on species and growing conditions) remains highly uncertain, particularly since traditional forestry-derived equations have been shown to underestimate whole-tree biomass in agroforestry systems, necessitating additional field work to further document biomass carbon allocation differences. Melson et al. (2011) noted in their forest-based research that estimation of live-tree carbon was sensitive to model selection (with an error of potentially 20 to 40 percent), and that model selection could be improved by matching tree form to existing equations. Zhou et al. (2015) found that whole-tree biomass for individual trees was underestimated by at least 18 percent in the Great Plains for three shelterbelt species, indicating that a correction factor could reduce uncertainty. At this point, a correction factor is not suggested for the method, and the estimates should be considered conservative. In addition, woody belowground biomass estimates are calculated using aboveground density allometry (Chojnacky et al., 2014), which has large uncertainties due to a lack of data. See chapter 6 for further discussion of the uncertainty of tree volume and biomass equations. The Tier 1 method for shrubs and vines relies on regional defaults that have significant uncertainty associated with the default coefficients.

Limitations: While there are major sources of uncertainty for the biomass C methods, there are no known limitations to its application to all croplands and grazing lands in the United States.

3.2.2 Litter Carbon Stock Changes

Most herbaceous biomass in the form of plant litter or crop residue decomposes within 1 year on the soil surface. Therefore, the influence of litter carbon stocks on atmospheric CO_2 is assumed to be insignificant once land-use change effects on biomass (and subsequent influence on soil carbon stocks) are addressed. Further methods development may be possible in the future.

For cropland or grazing land systems with trees, coarse woody debris and litter carbon should be estimated based on the forest methods in chapter 5. The loss of litter and coarse woody debris with the conversion from forestland to cropland and grazing land is also addressed in chapter 5.

3.2.3 Soil Carbon Stock Changes

Box 3-4. Method for Estimating Soil Carbon Stock Changes

Mineral Soils

- Use a stock difference approach (Ogle et al., 2019a) to estimate the change in SOC based on the amount of SOC at the beginning and end of the year. Estimate the stocks with the DayCent ecosystem model (Tier 3) or country-specific stock change factors (Tier 2) depending on the crops and soil conditions.
- Estimate the change in SOC from biochar carbon amendments as a net increase using an empirical method developed by IPCC (Ogle et al., 2019a).

Organic Soils

- Estimate SOC stock changes from the drainage of organic soils with the IPCC equation using country-specific emission factors (Tier 2) (Ogle et al., 2019a).

3.2.3.1 Description of Method

This method accounts for the influence of land use and management on SOC and associated CO_2 flux to the atmosphere for mineral soils using a carbon stock difference approach for all practices (Ogle et al., 2019a) except biochar amendments (see appendix 3A.2 for rationale). The stock difference method is based on estimating the amount of SOC (i.e., stock) at the beginning and end of the year, then subtracting the stocks to determine the change. Biochar amendments are estimated with a gain-loss method (i.e., estimating the inputs and outputs rather than the stock of biochar carbon in the soil) in which the net effect is a long-term gain of carbon in soils (Ogle et al., 2019a). As with biochar carbon, a gain-loss method is used to estimate carbon stock changes in organic soils (i.e., *Histosols*), but in this case, the net change is a loss of carbon from the soil due to drainage of the organic soil. If organic soils are not drained, there is minimal carbon loss for the land parcel. Emissions occur in organic soils following drainage due to the conversion of an anaerobic environment with a high-water table to aerobic conditions (Armentano and Menges, 1986), resulting in a significant loss of carbon to the atmosphere (Ogle et al., 2003).

Mineral Soils

The model to estimate changes in SOC stocks for mineral soils has been adapted from the method developed by IPCC (Ogle et al., 2019a). Use equation 3-8 to estimate the annual change in SOC stocks to a 30-centimeter depth, and net change in SOC from a biochar carbon amendment for a land parcel.

Equation 3-8: Change in SOC Stocks for Mineral Soils

$$\Delta TC_{mineral} = (\Delta C_{mineral} + \Delta SOC_{BC}) \times CO_2MW$$

Where:

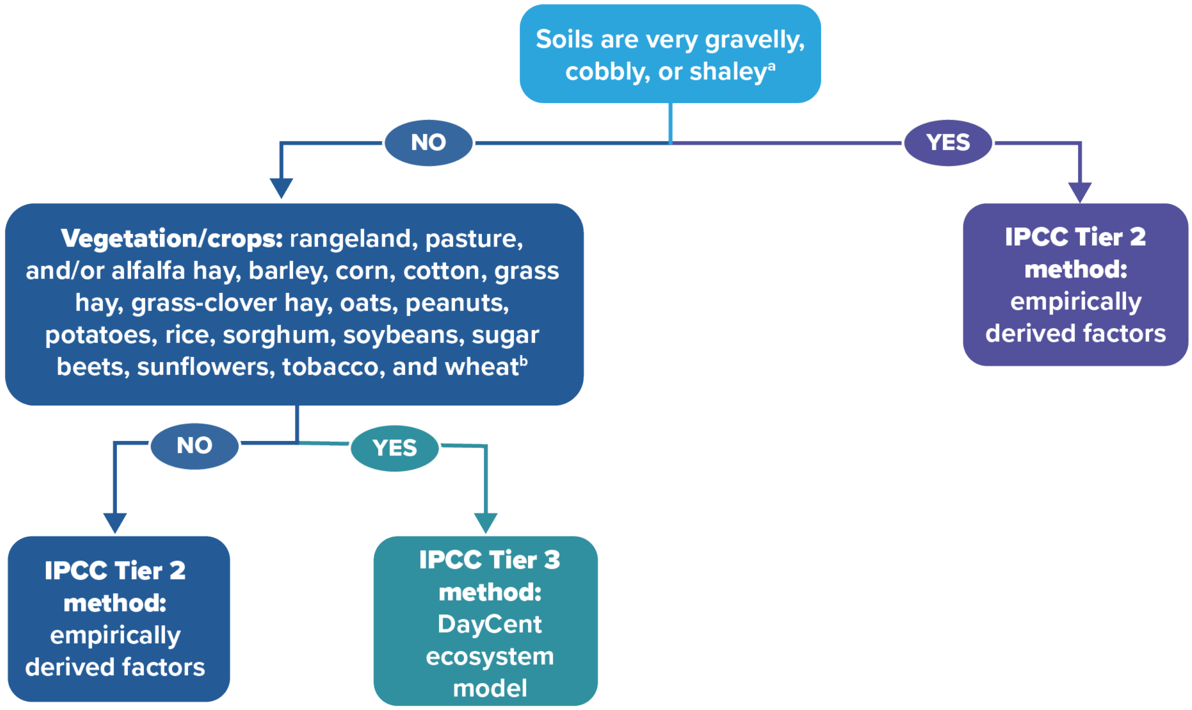
$\Delta TC_{mineral}$	=	annual change in mineral soil organic carbon stock plus biochar amendments (metric tons CO_2-eq)
$\Delta C_{mineral}$	=	annual change in mineral soil organic carbon stock (metric tons C)
ΔSOC_{BC}	=	annual change in soil organic carbon stock from biochar amendments (metric tons C)
CO_2MW	=	ratio of molecular weight of CO_2 to carbon = 44/12 (metric tons CO_2/metric tons C)

$$\Delta C_{mineral} = [(SOC_t - SOC_{t-1}) \div t] \times A$$

Where:

$\Delta C_{mineral}$	=	annual change in mineral soil organic carbon stock (metric tons C)
SOC_t	=	soil organic carbon stock at the end of the year (metric tons C/ha)
SOC_{t-1}	=	soil organic carbon stock at the beginning of the year (metric tons C/ha)
t	=	1 year for Tier 3 and 20 years for Tier 2
A	=	area of the parcel (ha)

Use a Tier 3 method (with the DayCent ecosystem model) or a Tier 2 method (with empirical stock change factors) to estimate the SOC stocks at the beginning and end of each year for equation 3-8. The Tier 3 method has been shown to have less uncertainty (U.S. EPA, 2020; Del Grosso et al., 2011), but has not been fully developed and/or tested for all soil types and crops that are grown in the United States. Accordingly, use figure 3-2 to choose the right method for a specific land parcel.



[a] Classified as soils whose volume is more than 35 percent gravel, cobbles, or shale.

[b] If other crops are grown in rotation with this set of crops, the IPCC Tier 2 method should be used to estimate soil C stock changes. Other crops may be included with the Tier 3 method if they are included in the Tier 3 method for future U.S. National GHG Inventories (published annually; most recent version is U.S. EPA, 2020). In addition, USDA may review and potentially approve crops for inclusion in the Tier 3 method if crop production can be simulated with reasonable accuracy using the DayCent model.

Figure 3-2. Decision Tree to Choose the Method for Estimating the SOC Stock Changes for a Land Parcel Using the $\Delta C_{mineral}$ From Equation 3-8

Tier 3 method: This method involves using the DayCent ecosystem model (note: DayCent is also used to estimate direct soil N_2O emissions for mineral soils—see section 3.2.4.1—using the same approach described in this section), consistent with the approach used for the U.S. National GHG Inventory (U.S. EPA, 2020). It involves a three-step process (in which the first two steps produce an estimate of initial SOC stocks prior to the reporting period):

- Run the model to a steady-state condition[5] (i.e., equilibrium) with native vegetation,[6] historical climate data,[7] and the soil physical attributes for the land parcel.
- Simulate a period from the mid-1800s to the most recent year prior to the first year in the reporting period. The entity chooses the practices that best match the land management of the parcel. In addition, the entity may enter more specific information about the management for the parcel during the last 30 years of the time series if available, including

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[5] The goal of the steady-state simulation is to set the state-variables (e.g., amount of C in the soil organic matter pools) in a range that is consistent with environmental conditions at the site.

[6] Broad vegetation types representing the dominant mixture of C_3 and C_4 grasses in grasslands and dominant forest types such as broadleaf deciduous or evergreen needleleaf.

[7] Historical data will depend on the time series, and PRISM has data from 1980 to the present. See section 3.2.3.3.

specific crops planted, tillage practices, fertilization practices, irrigation, and other management activity. Otherwise, the entity can choose from the general management options based on common regional practices (see section 3.2.3.2 for more information). The resulting carbon stock at the end of the simulation provides the initial baseline value *(SOC_{t-1})*.

- Estimate stocks during the reporting period based on the management activity for the land parcel. The entity provides the management activity for the land parcel, including crops planted, tillage practices, fertilization practices, irrigation, and other management activity data (see section 3.2.3.2 for more information). Apply the implicit model-based method to estimate uncertainty in the prediction of SOC stocks from the DayCent ecosystem model as discussed in section 3.2.3.4.

Estimate the change in SOC stocks by subtracting the initial SOC stock (i.e., SOC stock at the end of the previous year) *(SOC_{t-1})* from the stock at the end of the current year *(SOC_t)* for each year in the reporting period after applying the implicit model-based method (see section 3.2.3.4).

Estimate eroded carbon with RUSLE2 for water erosion (USDA, 2008) and WEPS for wind erosion (USDA, 2020). The amount of eroded SOC is reported separately from the DayCent model results for information purposes in order to consider uncertainty in the fate of eroded SOC as part of a mitigation program.[8]

Tier 2 method: The IPCC Tier 2 method is also consistent with the U.S. National GHG Inventory's approach (Ogle et al., 2003, 2006; U.S. EPA, 2020). It is based on a reference carbon stock under long-term cultivation, with stock change factors applied to estimate the change in stock given the land use (F_{LU}), management (F_{MG}), and organic matter input (F_I) for the land parcel. Estimate the SOC stock with country-specific factors using equation 3-9 for the land use, management, and input conditions during the reporting year and the conditions 20 years prior to the reporting year.[9]

Equation 3-9: SOC Stock for Mineral Soils Using the IPCC Tier 2 Method

$$SOC = SOC_{ref} \times F_{LU} \times F_{MG} \times F_I$$

Where:

SOC	=	soil organic carbon stock at the beginning (SOC_{t-1}) or end (SOC_t) of the year (metric tons C/ha)
SOC_{ref}	=	reference soil organic carbon stocks for U.S. agricultural lands in long-term cultivation (metric tons C/ha)
F_{LU}	=	stock change factor for land use (dimensionless)
F_{MG}	=	stock change factor for management regime (dimensionless)
F_I	=	stock change factor for the input of organic matter (dimensionless)

[8] Eroded SOC can be transferred laterally across the landscape and retained in the biosphere instead of emitted to the atmosphere as CO_2 (Van Oost et al., 2007; Wang et al., 2017).

[9] It is possible to estimate changes over less than 20 years, but the differences in stocks must be divided by 20 years, which is the stock change factor dependence as discussed in the IPCC guidelines (Ogle et al. 2019a). If the time frame is less than 20 years, it is also important to recognize that effects will continue into the next time period(s) in the analysis until 20 years has elapsed since the management, input or land-use change occurred.

The reference stocks for this equation are presented in table 3-9 and the stock change factors are provided in table 3-10. The U.S.-specific factors are based on a reference condition with long-term cultivation of the land (Ogle et al., 2003). The stock change factors for land use (F_{LU}) represent changes in land use, such as cultivated (i.e., annual crop production) to uncultivated land uses (e.g., perennial crops and grazing land), and setting aside land into the reserve from crop production. The stock change factors for management (F_{MG}) represent the effect of changing tillage in annual croplands and grazing intensity in grazing lands. The stock change factors for organic matter input (F_I) represent the influence of changing the input from crop or forage production, as well as the external organic matter additions, such as manure amendments. The change from the reference condition associated with land use, management, and input on the SOC stock over 20 years. Therefore, the stock at the beginning of the year *(SOC_{t-1})* is based on the previous management practices and land use before the entity adopted the current practices. If land use, management, and organic matter input have not changed for 20 years, the change in SOC stock ($\Delta C_{mineral}$ in equation 3-8) is equal to 0.

Table 3-9. Reference Carbon Stocks and 95-Percent Confidence Intervals for the United States (Metric Tons C/ha)

IPCC Soil Categories	USDA Taxonomic Soil Orders	Cold Temperate, Dry	Cold Temperate, Moist	Warm Temperate, Dry	Warm Temperate, Moist	Sub-Tropical, Dry	Sub-Tropical, Moist
High clay activity mineral soils	*Vertisols, Mollisols, Inceptisols, Aridisols,* and high base status *Alfisols*	42 (±2.7)	65 (±2.2)	37 (±2.2)	51 (±2.0)	42 (±5.1)	57 (±25.5)
Low clay activity mineral soils	*Ultisols, Oxisols,* acidic *Alfisols,* and many *Entisols*	45 (±5.9)	52 (±4.5)	25 (±2.7)	40 (±2.4)	39 (±9.4)	47 (±27.2)
Sandy soils	Any soils with greater than 70 percent sand and less than 8 percent clay (often *Entisols*)	24 (±9.4)	40 (±7.3)	16 (±4.7)	30 (±3.9)	33 (±3.7)	50 (±15.5)
Volcanic soils	*Andisols*	124 (±22.3)	114 (±32.7)	124 (±22.3)	124 (±22.3)	124 (±22.3)	128 (±29.4)
Spodic soils	*Spodosols*	86 (±12.7)	74 (±13.3)	86 (±12.7)	107 (±16.3)	86 (±12.7)	86 (±12.7)
Aquic soils	Soils with aquic suborder	86 (±22.3)	89 (±7.1)	48 (±7.1)	51 (±3.5)	63 (±3.7)	48 (±16.5)

Source: U.S. EPA, 2020.

Stocks represent the amount of SOC with long-term cultivation of the land parcel. The values in parentheses are 95-percent confidence intervals based on a normal distribution that can be used to propagate error through the analysis and quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there will be additional uncertainty with application of this method at the entity scale that is not quantified.

Table 3-10. Land Use, Management, and Input Factors and 95-Percent Confidence Intervals for the United States

Parameter	Subtropical Moist and Warm Moist Climate	Subtropical Dry and Warm Dry Climate	Cool Moist Climate	Cool Dry Climate
Land-Use Change Factors				
Cultivated[a]	1	1	1	1
Wetland rice production factor[b]	2.14±0.13	2.14±0.13	1.85±0.15	1.85±0.15
General uncultivated	1.58±0.12	1.58±0.12	1.37±0.15	1.37±0.15
Set-asides	1.18±0.19	1.18±0.19	1.05±0.24	1.05±0.24
Cropland Management Factors				
Full intensive till[a]	1	1	1	1
Reduced till	1.05±0.08	1.00±0.09	1.05±0.08	1.00±0.09
No-till	1.14±0.06	1.09±0.07	1.14±0.06	1.09±0.07
Cropland Input Factors				
Low	0.94±0.02	0.94±0.02	0.94±0.02	0.94±0.02
Medium[a]	1	1	1	1
High	1.07±0.04	1.07±0.04	1.07±0.04	1.07±0.04
High with amendment[c]	1.44±0.19	1.37±0.16	1.44±0.13	1.37±0.16
Grazing Land Management Factors[c]				
Native or nominally managed grazing lands[a]	1	1	1	1
Improved	1.14±0.25	1.14±0.25	1.14±0.25	1.14±0.25
Moderately degraded	0.90±0.14	0.90±0.14	0.90±0.14	0.90±0.14
Severely degraded	0.70±0.55	0.70±0.55	0.70±0.55	0.70±0.55
Grazing Land Input Factors[c]				
Improved with medium input[a]	1	1	1	1
Improved with high input	1.11±0.15	1.11±0.15	1.11±0.15	1.11±0.15

Source: U.S. EPA, 2020.

The values in parentheses are 95-percent confidence intervals based on a normal distribution that can be used to propagate error through the analysis and quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there will be additional uncertainty with application of this method at the entity scale that is not quantified.

[a] Uncertainty is not applicable because it is already incorporated into the reference carbon stock.

[b] U.S.-specific factors are not estimated for wetland rice production due to a lack of studies addressing the impacts in the United States. Factors provided by IPCC for the Tier 1 method (Ogle et al., 2019b) are used as the best estimates of these impacts. This factor was derived by combining the land-use change factor for general uncultivated (in this table) and the rice cultivation factor from the IPCC guidelines. Management and input factors are set to 1 for rice cultivation.

[c] U.S.-specific factors are not estimated for high input with organic amendment for croplands, or for grazing land management, due to a lack of studies addressing the impacts in the United States. Factors provided by IPCC for the Tier 1 method (Ogle et al., 2019b; McConkey et al., 2019) are used as the best estimates of these impacts.

Apply the stock change factors in table 3-10 to a land parcel based on the previous 5 years of cropping history, using the following guidance:

- Land-use change factors. For land use, apply the cultivated factor to parcels that were cultivated with tillage for annual crop production or mixed annual crops and perennial rotations, such as hay or pasture in rotation with annual crops, during the previous 5 years. Apply the land use factor for wetland rice production to parcels with continuous wetland rice production during the previous 5 years. If the parcel had some rice production but was not continuously used for the production of rice during the previous 5 years, then apply the cultivated land factor. Apply the general uncultivated land factor for other land uses or nonannual crop management systems, such as grazing land, perennial hay crops, perennial tree crops, and agroforestry. Apply the set-aside factor to land parcels set aside from production during the past 5 years for up to 20 years. Following 20 years, apply the general uncultivated factor to such parcels.

- Cropland management factors. Management factors are based on tillage management in croplands. The factors are applied to land parcels in cropland based on the most intensive tillage practice during the last 5 years, even if the practice is only applied in 1 year (full intensive till > reduced till > no-till). Therefore, the estimation will only include no-till if there is continuous adoption over the entire 5 years and reduced till if there is continuous reduced till or a combination of reduced till and no-till.
- Cropland input factors. Input factors in croplands are based on the IPCC classification for cropland systems (Ogle et al., 2019b; see figure 5-1 for a classification diagram) according to crop selection and rotation practices in addition to the level of inputs to enhance production in croplands. Input classifications include low, medium, high and high with amendments. Guidance for selecting the appropriate input factor is provided below.
    - Assign the low input factor to the land parcel if residues were removed or burned in 2 or more of the 5 previous years unless there was a manure amendment in 2 or more of the 5 previous years. In that case, use the medium input factor. Also assign low input if a parcel's crops produced low amounts of residue, i.e., low residue crop, following harvest in 2 or more of the previous 5 years or if there are 2 or more years of bare-summer fallow in the previous 5 years. For example, vegetable or fiber crops such as cotton and tobacco are low residue crops; see table 3-11 for a list of low- vs. medium-/high-residue crops. However, assign medium input if these land parcels received a manure amendment or cover crops in at least 2 of the previous 5 years, or are managed with a rotation of mixed annual crops and perennials—for example, hay or pasture in rotation with annual crops.
    - If mineral fertilizers were not applied to a parcel during the previous 5 years, this should be considered low input. Even if fertilizers are not applied, the cropping system is medium input if the entity applied manure amendments or irrigation, has grown cover crops, or has grown higher-yielding varieties in 2 or more of the previous 5 years, or if the parcel was managed with mixed annual crops and perennial rotation in the previous 5 years.
    - Assign medium input to all other cropland parcels, with two exceptions: (1) for land parcels with manure amendments in 2 or more of the previous 5 years, assign high input with organic amendments; and (2) assign high input if the entity used irrigation, had cover crops, and/or had a more productive crop variety for 2 or more years in the previous 5 years, or if the land parcel is managed with a rotation of mixed annual crops and perennials, such as hay or pasture in rotation with annual crops.

Table 3-11. Classification of Crops Into Low, Medium, or High Residue Production Categories for Estimation of Input Factors in the Tier 2 Soil Carbon Method

Crop	Classification
Barley	Medium
Beans	Medium
Corn grain	High
Corn silage[a]	Low
Cotton	Low
Millet	Medium
Oats	Medium
Peanuts	Medium
Potatoes	Low
Rice	High
Rye	Medium
Sorghum grain	High
Sorghum silage[a]	Low
Soybean	Medium
Sugar beets	Low
Sugarcane	High
Sunflower	Medium
Tobacco	Low
Wheat	Medium
Alfalfa hay	High
Nonlegume/grass hay	High
Vegetables	Low
Other crops	Medium

[a] Silage crops are assumed to have low residue production, but these crops can be classified as medium if 25 percent or more of the biomass is left as residue following harvest.

- Grazing land management factors. For grazing land, management factors are based on the level of improvement or degradation in the land parcel. Degradation is largely determined by reduction in production potential/ecological function/biological integrity of an ecological site due to disturbance resulting in phase shifts and/or state change in the USDA-NRCS ecological state-and-transition model from the reference state condition (USDA, 2017). Moderately degraded factors are applied to the land parcel if disturbance shifts vegetation composition and moderate loss in forage production occurs (i.e., phase shifts or state changes where reversal of the disturbance can result in a restoration pathway to the original state with external inputs or management). Severely degraded factors are applied to land parcel if disturbance induces an ecological state change with a large loss of forage production that also requires external inputs and/or management to return the plant community back to the Reference Plant Community of the ecological site because there is no restoration pathway to restore the site productivity. If the grazing land parcel is not degraded, then improvements can lead to more production and more SOC. The improved management factor is applied to the land parcel improved with a single management factor. Improvements may include fertilization, planting more productive forage species than is typical for the region, irrigation, liming, and inter-seeding legumes with grass forage species.

- Grazing land input factors. Determine input categories for grazing lands by the level of improvement to the grazing land if there is no degradation. Medium-input grazing land has a single improvement (e.g., fertilization, irrigation, or growing more productive forage species than is typical for the region or moving to a more productive/higher functioning phase or ecological state compared to the reference state condition in the ecological state and transition model) and a light to moderate grazing regime based on recommended stocking rates in the local area. The input factor is 1 for medium input because the effect of a single improvement is represented by the management factor for improved grazing land management. Assign high input if a land parcel is managed with more than one improvement and there is a light to moderate grazing regime.

Biochar carbon amendments: As described by Woolf et al. (2021), estimate the change in SOC stocks associated with biochar amendments to soils with equation 3-10, a method originally developed by IPCC (Ogle et al., 2019a). The long-term carbon gain is calculated as the product of the mass of biochar added to the soil *(M_{bc})*, its carbon fraction *(F_c)*, and the fraction that will persist un-mineralized over 100 years *(F_{perm})*.

Equation 3-10: Change in SOC Stocks for Mineral Soils from Biochar Amendments

$$\Delta SOC_{BC} = M_{bc} \times F_C \times F_{perm}$$

Where:

ΔSOC_{BC}	=	annual change in mineral soil organic carbon stock from biochar amendments (metric tons C)
M_{bc}	=	mass of biochar added to soil in a year (metric tons biochar)
F_C	=	carbon fraction of biochar (metric tons C/metric tons biochar)
F_{perm}	=	fraction of biochar carbon remaining after 100 years (metric tons C/metric tons C)

Values of F_C are provided in table 3-12, disaggregated by feedstock type and production technology (pyrolysis or gasification).

Table 3-12. Carbon Fraction *(F_C)* of Biochar and 95-Percent Confidence Intervals From Various Feedstock Types Through Either Pyrolysis or Gasification

Feedstock	Production Technology	F_c
Manure	Pyrolysis	0.36 (±0.18)
	Gasification	0.09 (±0.04)
Wood	Pyrolysis	0.73 (±0.33)
	Gasification	0.52 (±0.27)
Herbaceous biomass[a]	Pyrolysis	0.61 (±0.29)
	Gasification	0.28 (±0.14)
Rice residue[b]	Pyrolysis	0.46 (±0.20)
	Gasification	0.13 (±0.06)

Feedstock	Production Technology	F_c
Nut shells, pits, and stones	Pyrolysis	0.70 (±0.29)
	Gasification	0.40 (±0.22)
Biosolids[c]	Pyrolysis	0.33 (±0.14)
	Gasification	0.07 (±0.04)

Source: Estimated using regression from Neves et al. (2011), corrected for ash content using biochar yield from Woolf et al. (2014). The confidence intervals represent uncertainty for an entity scale application of the method.

F_C is given on a dry mass basis. The values in parentheses are 95-percent confidence intervals based on a normal distribution that can be used to propagate error through the analysis and quantify uncertainty.

[a] Herbaceous feedstocks include grasses, forbs, and leaves, but not rice hulls and rice straw.

[b] Rice residues include both rice hulls and rice straw.

[c] Biosolids include both paper sludge and sewage sludge.

Estimate the F_{perm} factor using equation 3-11, as a function of the molar weight of hydrogen to organic carbon ratio of the biochar atomic composition (Woolf et al., 2021).

Equation 3-11: Equation to Estimate the Permanence Factor for Biochar Amendments to Soils

$$F_{perm} = 1.09 - 0.6 \times H{:}C_{org}$$

Where:

F_{perm}	=	fraction of biochar carbon remaining after 100 years (metric tons C/metric tons C)
$H{:}C_{org}$	=	molar ratio of the H to the organic carbon content of the biochar amendment (mol H/mol organic C) (valid values range between 0.15 and 0.7)

Parameter standard deviations: 1.09 (±0.06), 0.6 (±0.09)

Organic materials with a value of $H{:}C_{org}$ greater than 0.7 are not persistent enough to be classified as biochar for the purposes of long-term carbon sequestration. Accordingly, amendments with $H{:}C_{org}$ above 0.7 are not to be treated as biochar, but should be treated as organic matter additions in the mineral soil calculation methodology in equation 3-8 ($\Delta C_{mineral}$). In addition, $H{:}C_{org}$ values below 0.15 are not typical of biochar, and in this case, the $H{:}C_{org}$ value should be set to 0.15. There may be more C storage with $H{:}C_{org}$ values less than 0.15, but research is needed to estimate the additional amount beyond the level with a $H{:}C_{org}$ value of 0.15.

Organic Soils

The methodology for estimating soil carbon stock changes in drained organic soils has been adopted from IPCC (Ogle et al., 2019a). The method applies to *Histosols* and soils that have high organic matter content and are developed under saturated, anaerobic conditions for at least part of the year, including *Histels, Historthels,* and *Histoturbels*. Use equation 3-12 to estimate emissions from a land parcel.

Equation 3-12: Change in SOC Stocks for Organic Soils

$$\Delta C_{Organic} = A \times EF \times CO_2MW$$

Where:

$\Delta C_{Organic}$	=	annual CO_2 emissions from drained organic soils in crop and grazing lands (metric tons CO_2-eq)
A	=	area of drained organic soils (ha)
EF	=	annual emission factor (metric tons C/ha)
CO_2MW	=	ratio of molecular weight of CO_2 to C = 44/12 (metric tons CO_2/metric tons C)

Emission factors have been adopted from the U.S. National GHG Inventory (U.S. EPA, 2020; Ogle et al., 2003) and are region-specific and based on typical drainage patterns and climatic controls on decomposition rates. Drained organic soils in cropland lose carbon at rates presented in table 3-13. Organic soils in grazing lands are typically not drained to the depth of cropland systems, and therefore the emission factors are only 25 percent of the cropland values (Ogle et al., 2003). The carbon loss rate will be 0 if organic soils are not drained for crop production or grazing. However, CH_4 emissions will need to be estimated for these systems if they are not drained, particularly if they are used for rice cultivation (see section 3.2.6). The emission factors are provided in table 3-13.

Table 3-13. Emission Factors and 95-Percent Confidence Intervals for Organic Soils (i.e., *Histosols*) That Are Drained in Cropland and Grazing Land in the United States

Emission Factor for Drained Organic Soils (metric tons C/ha)	Cool Temperate Climate	Warm Temperate Climate	Subtropical Climate
Cropland	11.2 (±2.5)	14.0 (±2.5)	14.3 (±6.5)
Grazing land	2.8 (±1.3)	3.5 (±1.3)	3.6 (±3.3)

Source: U.S. EPA, 2020.

The values in parentheses are 95-percent confidence intervals based on a normal distribution that can be used to propagate error through the analysis and quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

Box 3-5. Projecting Soil Carbon Stock Changes

For the estimation of future soil carbon stock changes, the methods described in this section can be applied with the DayCent model and Tier 2 methods in combination with expected management practices. For DayCent simulations, the previous 10 years of weather are repeated for the projections. The equations should be applied in a baseline scenario and the mitigation scenario: the difference in stocks between the two scenarios is an estimate of the technical mitigation potential for the land parcel. Biochar carbon stock changes can be approximated based on the rate and type of future biochar amendments using equations in this section. Projections should only be used for planning; reporting, estimate stock changes from the land parcel with the actual weather and management practices. Other considerations—e.g., the cost of adopting a new practice, and issues surrounding permanence and leakage—are not addressed with these methods but may also influence the amount of GHG mitigation.

3.2.3.2 Activity Data

Overview of Requirements

Activity data requirements are different for mineral soils and organic soils. For mineral soils, the method for croplands requires the following management activity data to estimate $\Delta C_{mineral}$ (as described in equation 3-8).

Croplands

Some requirements are common to the Tier 3 and Tier 2 methods for mineral SOC stock changes:

- Area of land parcel (i.e., field)
- Crop types and rotation sequence
- Residue management, including proportion harvested, burned, grazed, or left in the field
- Mineral fertilization (yes/no)
- Organic amendments (yes/no)
- Tillage implements and number of passes in each operation[10]
- Use of irrigation (yes/no)
- Cover crop (yes/no)

The additional information needed for the Tier 3 method using the DayCent process-based model[11] includes:

- Planting and harvesting dates
- Mineral fertilizer type (including enhanced-efficiency fertilizers with nitrification inhibitors or polymer-coated fertilizers), application rate, application method (broadcast, banded, fertigation), and timing of application(s)
- Organic amendment type (e.g., manure and composted manure by livestock type, other organic fertilizers), and application rate, method and timing of application(s)
- Timing of tillage operations
- Months of the year when land parcel is irrigated
- Use of drainage practices and depth of drainage (common in hydric soils)
- Cover crop types, planting and harvesting dates, and termination method

The additional information needed for the Tier 2 method for biochar C amendments includes:

- Type and amount of biochar application, and $H{:}C_{org}$ ratio of biochar

The method for croplands on organic soils requires the following activity data to estimate $\Delta C_{Organic}$ in equation 3-12.

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[10] Use this information to determine tillage intensity (i.e., intensive till, reduced till, and no-till), using the classification applied in the U.S. National GHG Inventory. See section 3.2.3.2 for more information about the tillage classification.

[11] The data requirements for the Tier 3 method are to estimate SOC stock changes and soil N_2O emissions (See section 3.2.4.2).

- Area of drained organic soils on the land parcel (i.e., field)

Grazing Lands

Some of the activity data requirements for grazing land are common to the Tier 3 and Tier 2 mineral soil C stock change methods for croplands. The activity data requirements for grazing land include:

- Area of the land parcel (i.e., field)
- Forage type (perennial grass such as cool or warm season grasses, legume, or mixed grass-legume nitrogen-fixing species)
- Mineral fertilization (yes/no)
- Organic amendments (yes/no)
- Use of irrigation (yes/no)

The additional information needed for the Tier 3 method using the DayCent process-based model includes:

- Mineral fertilizer type (including enhanced-efficiency fertilizers with nitrification inhibitors or polymer-coated fertilizers) and application rate
- Organic amendment type (e.g., manure and composted manure by livestock type, other organic fertilizers), and application rate
- Months of the year with grazing
- Animal type and stocking rates
- Grazing method (continuous, rotational grazing, or other type)
- Months of the year when land parcel is irrigated
- Use of drainage practices and depth of drainage ((e.g., drainage to improve grazing conditions in hydric soils)
- Tillage implements and timing of tillage operations, and/or timing of herbicide applications for renewal of forage grazing land, in addition to the timing and type of forage that is replanted or naturally regenerates on the land parcel

The additional information needed for the Tier 2 mineral SOC stock change method includes:

- Current ecological site and the reference condition for the land parcel based on the USDA-NRCS ecological state and transition model framework. The reference and alternative states are available through the USDA-NRCS web soil survey[12] The method for grazing lands on organic soils requires the following activity data to estimate $\Delta C_{Organic}$ in equation 3-12.
- Area of drained organic soils on the land parcel (i.e., field)

[12] If the information is not available through the USDA-NRCS web soil survey, then the entity should contact USDA-NRCS extension office for guidance on identifying the current and reference conditions.

Additional Notes on Activity Data Requirements

Tillage is categorized into full intensive tillage, reduced till, and no-till depending on the tillage implements and the number of passes. The tillage systems are classified based on the most intensive practice during the previous 5 years.

- Full intensive tillage is a full inversion or mixing of the soil with implements such as a moldboard plow or deep disking; it leaves low surface residue coverage.
- No-till is defined as not disturbing the soil with mixing or inversion, creating only minor disturbances at the soil surface with seed drills.
- The remainder of the cultivated area is classified as reduced till and includes practices such as mulch tillage and ridge tillage.

Tillage intensity is estimated for the planting period and the post-harvesting period. For the Tier 3 method, the intensities for each period are simulated with the model, using an intensity ranking from A to K. For the Tier 2 method, the tillage intensity is estimated for the entire year and classified into broad categories (i.e., no-till, reduced till, and full intensive till) that are used for assigning tillage management factors. The following table provides the tillage system intensity for each tillage category, in addition to the intensity categories that are used in the Tier 3 method.

Table 3-14. Tillage Categories, Intensity Categories for the Tier 3 Method, and Tillage Intensity Ranges

Tillage Category	Intensity Categories—Tier 3 Method	Tillage System Intensity Range
No-till	A	0.001–0.01
	B	0.011–0.04
	C	0.041–0.075
Reduced till	D	0.076–0.111
	E	0.112–0.144
	F	0.145–0.162
	G	0.163–0.202
	H	0.203–0.252
Full intensive till	I	0.253–0.268
	J	0.269–0.449
	K	0.450–1.00

Estimate tillage system intensity using equation 3-13.

The calculation in equation 3-13 starts with the implement that has the effect to the shallowest depth *(T_1)*, then proceeds with the calculation for each additional implement (T_2 to T_n) in order of tillage depth from shallow to deepest implement. If two or more implements have the same tillage depth, calculate the tillage intensity in order from least to most intensive implement. This calculation assumes that each additional tillage implement that mixes the soil does not have a significant impact on the decomposition of SOC in the proportion of the soil in the upper layers that previous implements have already disturbed. In addition, the influence of shallower tillage implements (e.g., T_1) cannot exceed the depth of the next tillage implement in the sequence (e.g., T_2). The tillage intensity cannot be negative.

Equation 3-13: Tillage System Intensity

$$TI = \frac{\sum_{t \to n} T_t}{30}$$

$$T_1 = ME_1 \times D_1$$

$$T_2 = ME_2 \times (D_2 - T_1)$$

$$T_n = ME_n \times (D_n - T_1 - \ldots T_{n-1})$$

Where:

TI	=	tillage system intensity for all implements used in planting or post-harvesting period to a depth of 30 cm
T_t	=	tillage intensity for each implement, 1 to n implements (proportion of disturbance)
ME_n	=	mixing efficiency of an implement (proportion of disturbance)
D_t	=	depth of the tillage for an implement (cm)

The mixing efficiencies and soil depth of tillage for each implement are provided below in table 3-15 and are also available in appendix table A-9 of the Soil and Water Assessment Tool (SWAT) model documentation (Arnold et al., 2012).

Table 3-15. Mixing Efficiencies and Tillage Depths From Common Implements

Implement Description	Mixing Efficiency	Tillage Depth (cm)
Bed Roller	0.25	5
Bedder (Disk)	0.55	15
Bedder Disk-Hipper	0.65	15
Bedder Disk-Row	0.85	10
Bedder Shaper	0.55	15
Beet Cultivator	0.25	2.5
Blade 10 ft	0.25	7.5
Chisel Plow	0.3	15
Coulter-Chisel	0.5	15
Crust Buster	0.1	6
Culti-Mulch Roller	0.25	2.5
Culti-Packer Pulverizer	0.35	4
Cultiweeder	0.3	10
Deep Ripper-Subsoiler	0.25	35
Discovator	0.5	2.5
Disk Border Maker	0.55	15
Disk Chisel (Mulch Tiller)	0.55	15
Disk Plow	0.85	10
Duckfoot Cultivator	0.55	10
Field Conditioner (Scratcher)	0.1	6
Field Cultivator	0.3	10

Implement Description	Mixing Efficiency	Tillage Depth (cm)
Finishing Harrow	0.55	10
Flex-Tine Harrow	0.2	2.5
Float	0.1	6
Furrow Diker	0.7	10
Furrow-Out Cultivator	0.75	2.5
Harrow (Tines)	0.2	2.5
Hipper	0.5	10
Land Plane-Leveler	0.5	7.5
Landall, Do-All	0.3	15
Laser Planer	0.3	15
Levee-Plow-Disc	0.75	2.5
Leveler	0.5	2.5
Lister (Middle-Buster)	0.15	4
Marker (Cultivator)	0.45	10
Middle Buster	0.7	10
Moldboard Plow Reg	0.95	15
Multi-Weeder	0.3	2.5
Offset Disk-Heavy Duty	0.7	10
Offset Disk-Light Duty	0.55	10
One-Way (Disk Tiller)	0.6	10
Packer	0.35	4
Paraplow	0.15	35
Power Mulcher	0.7	5
Powered Spike Tooth Harrow	0.4	7.5
Rice Roller	0.1	5
Ripper	0.25	35
Rod Weeder	0.3	2.5
Roller Groover	0.25	6
Roller Harrow	0.4	6
Roller Packer	0.05	4
Roller Packer Flat Roller	0.35	4
Rolling Cultivator	0.5	2.5
Rotary Hoe	0.1	0.5
Roterra	0.8	0.5
Roto-Tiller	0.8	0.5
Rotovator-Bedder	0.8	10
Row Conditioner	0.5	2.5
Row Cultivator	0.25	2.5
Rowbuck	0.7	10
Rubber-Wheel Weed Puller	0.35	0.5
Sand-Fighter	0.7	10

Implement Description	Mixing Efficiency	Tillage Depth (cm)
Seedbed Roller	0.7	10
Single Disk	0.45	10
Soil Finisher	0.55	7.5
Spike Tooth Harrow	0.25	2.5
Springtooth Harrow	0.35	2.5
Stubble-Mulch Plow	0.15	7.5
Subsoil Chisel Plow	0.45	35
Subsoiler-Bedder Hip-Rip	0.7	35
Tandem Disk Plow	0.55	7.5
Tandem Disk Reg	0.6	7.5
Triple K	0.4	10
V-Ripper	0.25	35

Source: Arnold et al., 2012.

Box 3-6. Examples of Tillage Intensity Estimation

Tillage intensity is estimated using equation 3-13 and the information in table 3-14.

For example, a single tillage event with a duck cultivator, which has a mixing efficiency of 0.55 to a depth of 10 centimeters, apply the equation as follows:

$$Tillage\ Intensity = (0.55 \times 10) \div 30 = 0.183$$

A result of 0.18 is classified as a reduced tillage system with an intensity ranking of G (table 3-14).

Here is a second example based on two cultivation events in the planting period of the year. The first cultivation event is a tandem disk plow with a mixing efficiency of 0.55 to a depth of 7.5 centimeters; the second is a row conditioner with a mixing efficiency of 0.5 to a depth of 2.5 centimeters.

$$Tillage\ Intensity = \{[0.5 \ \times 2.5] + [0.55 \ \times (7.5 - \ (0.5 \ \times 2.5))]\} \div 30 = 0.156$$

This is classified as a reduced tillage practice with an intensity ranking of F. Note that T_1 and T_2 are calculated within the square brackets.

For the Tier 3 method, the long-term history of site management is used to simulate initial SOC stocks for the crop or grazing system. To estimate the initial values, the entity will need to choose the most likely management for the land parcel over the previous 30 years prior to the reporting period. The entity may provide more specific information about the management of the parcel if available. The entity must also provide the previous land use and year of conversion if a land-use change occurred during the past three decades. Historical data for activity from more than three decades in the past will be represented based on national agricultural statistics using enterprise budgets and census data for various regions in the country. However, an entity can also provide the history prior to the last three decades if it is known.

Grazing method and timing are important for determining which parcels are grazed at different times of the year and the intensity of the grazing. Grazing is scheduled on a monthly basis to capture effects on forage production and the amount of manure C and N excreted directly onto land by livestock and not collected or managed (de Klein et al., 2006), referred to as Pasture/Range/Paddock (PRP) manure. Animal type influences manure C and N content. The amount of PRP manure nitrogen is estimated with the livestock methods (see section 4.5), and it is assumed that half of nitrogen is in urine and the other half in solids. The carbon content of the PRP manure is calculated based on carbon to nitrogen ratios of the manure, which can be estimated with the values in table 3-16. In addition, the lignin content of the manure is also needed because the amount of lignin influences the decomposition of the manure and incorporation into soil organic C. The lignin contents are provided in table 3-16.

Managed manure and other types of organic matter may be added to soils as amendments. The entity will provide data on the carbon and nitrogen content of organic amendments as well as lignin contents. Table 3-16 below provides defaults in case the entity does not have this information.

Table 3-16. Nitrogen and Carbon Fractions of Common Organic Fertilizers and Manure—Midpoint and 95-Percent Confidence Interval in Parentheses (Percent by Weight)

Organic Fertilizer	N (%)[a]	C (%)	Lignin (%)
Poultry manure	2.25 (1.5–3)	8.75 (7–10.5)[b]	5.1 (1.7–8.4)[f]
Pig, horse, and cow manure	0.45 (0.3–0.6)	5.1 (3.4–6.8)[c]	10.1 (1.8–18.4)[f]
Green manure	3.25 (1.5–5)	42 (40–45)[d]	14.4 (9.8–18.9)[g]
Compost	1.25 (0.5–2)	16 (12–20)[e]	39 (7–70)[h]
Sewage sludge/Biosolids	3 (1–5)	11.7 (3.9–19.5)[b]	2.8 (1.9–3.7)[i]

The 95-percent confidence intervals are based on a triangle distribution that can be used to propagate error through the analysis and quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

Sources:

[a] Hue, n.d.

[b] USDA, 1992.

[c] U.S. EPA, 2013. Weighted U.S. average carbon:nitrogen ratio for manure available for application.

[d] Assumes dry matter is 42 percent carbon, with an uncertainty based on the authors' expert opinion.

[e] A1 Organics, n.d.

[f] Meneses-Quelal et al., 2020.

[g] Tripolskaja et al., 2014.

[h] Tuomela et al., 1999. The amounts are highly variable depending on the level of decomposition in the composting process, leading to large uncertainties.

[i] Rowell et al., 2001.

For biochar amendments to mineral soils, the entity will need the following activity data for croplands or grazing lands to estimate SOC_{BC} in equation 3-10:

- Mass of biochar added to cropland soil
- Molar hydrogen to organic carbon ratio of the biochar
- Biochar feedstock type
- Biochar production technology (pyrolysis or gasification)

3.2.3.3 Ancillary Data

Ancillary data for the mineral soil method include historical weather patterns and soil characteristics. Weather data may be based on national datasets such as the Parameter-Elevation

Regressions on Independent Slopes Model, or PRISM (PRISM Climate Group, 2018). Soil characteristics may also be based on national datasets such as the Soil Survey Geographic Database, or SSURGO (Soil Survey Staff, 2023). For the Tier 2 method, the weather and soil data are used to classify the climate and soil type for each land parcel based on IPCC classifications (Reddy et al., 2019). The erosion model also requires ancillary data on topography (i.e., slope), length of the field and row orientation, crop canopy height, diversions, surface residue cover, and soil texture.

No ancillary data are needed to estimate the SOC changes from biochar amendments and drainage of organic soils.

3.2.3.4 Limitations and Uncertainty

Mineral Soils

Tier 3 Method: Use the implicit model-based method to estimate uncertainty for mineral soil C based on the Tier 3 method (see chapter 8). Uncertainty is associated with the DayCent ecosystem model due to the process-based model structure and parameters. Uncertainty is quantified with an empirically based approach, as used in the U.S. National GHG Inventory (Ogle et al., 2007; U.S. EPA, 2020). The method combines modeling and measurements to estimate SOC stock changes for entity-scale reporting (Conant et al., 2011). To calculate model uncertainty, entities may utilize values from a national soil monitoring network as described in Spencer et al. (2011), or from agricultural experiments (see U.S. EPA, 2020, for examples associated with the DayCent ecosystem model).

Uncertainty is assumed to be minor for the management activity data provided by the entity, and therefore the values are assumed to be certain. Uncertainties associated with model structure and parameters are quantified using an empirical method, as discussed above. The empirical method is based on a linear mixed-effect model that is given in equation 3-14, along with the covariance matrix for the fixed effects.[13] This model is applied M number of times to produce replicates of SOC stocks that can be used to determine the median and 95-percent prediction interval. Note that the same set of random draws, i.e., M random draws, for fixed effects and the random effects for region[14] and site are used in the calculation of SOC stocks in each year of the time series for a land parcel. In contrast, the M replicates of the residual error are redrawn in each year of the time series for a land parcel.[15] See chapter 8 for more information about how to propagate uncertainty using the implicit model-based method.

[13] The empirical model may be revised if the structure and/or parameterization of the DayCent ecosystem model is modified for the U.S. National GHG inventory to ensure that entity-scale reporting is consistent with national inventory methods.

[14] The region effect is based on Conservation Effects Assessment Project (CEAP) regions.

[15] The random effects for region and site within region will cancel when subtracting the stocks from 2 years for an individual land parcel, but the residual error will not cancel for the land parcel. The regions are based on the classification of agroecological regions in the Conservation Effects Assessment Project (https://www.nrcs.usda.gov/ceap).

Equation 3-14: Empirical Uncertainty Model for Quantifying Uncertainty in the Tier 3 Method for Mineral Soils

$$SOC = \exp\{3.4916 + (0.581 \times \ln SOC_{DayCent}) + b^{(r)}\} \div 100$$

Where:

SOC	=	soil organic carbon stock at the beginning (SOC_{t-1}) or end (SOC_t) of the ear (metric tons C/ha)
$\ln SOC_{DayCent}$	=	natural log of the predicted soil organic C stock from the DayCent Ecosystem Model (g C/ m^2)
$b^{(r)}$	=	sum of random effects associated with region and site within region, in addition to residual error from the linear mixed effect model. The random effects and residual error are drawn from a normal distribution with a mean of 0 and the following standard deviations, region = 0.1858, site within region = 0.3588, and residual error = 0.1401.
100	=	conversion from grams C/m^2 to metric tons C/ha

The implicit model-based method also requires the following covariance matrix:

	Intercept	$\ln SOC_{DayCent}$
Intercept	0.057361	-0.00621
$\ln SOC_{DayCent}$	-0.00621	0.000736

To reduce uncertainty, annual changes can be aggregated across land parcels by summing SOC stock changes within iterations in the Monte Carlo analysis across parcels (and entities), and then extracting the median and constructing a 95-percent prediction interval. (see box 8-2 in chapter 8). A similar process can also be used to aggregate annual estimates of SOC stock changes to produce results for multiple years (e.g., change over 5 or 10 years). Uncertainties are larger at finer spatial and temporal scales due to random effects and residual error that is reduced as the calculations incorporate SOC stock changes from more land parcels and/or years. Aggregation is a way to manage uncertainty and limit risk associated with programs that include the sequestration of carbon in agricultural soils as a mitigation pathway. See Ogle et al. (2010) for uncertainty at different scales of aggregation in which uncertainties can be over 100 percent at the entity scale, but significantly reduced with aggregation of farms and ranches to larger spatial scales and aggregating annual estimates to 5 or more years.

There are several additional uncertainties in the Tier 3 method, including no assessment of the effect of land use and management in subsurface layers of the soil profile (below 30 centimeters), no assessment of the transport and deposition of eroded carbon, and limited data to assess uncertainty in the parameters and structure of DayCent using the empirically based method. These limitations may lead to inaccurate estimates of the management effects on SOC stock changes and may be improved in the future with additional research and development.

Tier 2 method: Use the explicit model-based method to estimate uncertainty for the Tier 2 method (see chapter 8). Uncertainty is assumed to be minor for the management activity data provided by the entity, and therefore the values are assumed to be certain. Uncertainties in stock change factors are provided in table 3-9 and table 3-10 of section 3.2.3.1, and are propagated through the calculations using a Monte Carlo simulation. See chapter 8 for more information about the explicit model-based method.

Additional uncertainty in the Tier 2 method for mineral soils is due to the lack of specificity in local conditions for land parcels in croplands and grazing lands. This method was developed for national inventories (Ogle et al., 2003), so it does not address the finer-scale drivers of SOC stock changes on individual farms. There is also additional uncertainty in the estimation of annual changes given that this method represents effects over 20 years rather than on an annual basis. Consequently, the resulting estimates of SOC stock changes will be more accurate if results are aggregated across hundreds of farms and across a 20-year time series.

Biochar C – Tier 2 Method: Use the explicit model-based method to estimate uncertainty for the biochar C method (see chapter 8). Uncertainty is assumed to be minor for the management activity data provided by the entity, and therefore the values are assumed to be certain. Uncertainties in the parameters are provided in section 3.2.3.1, and are propagated through the calculations using a Monte Carlo simulation. See chapter 8 for more information about the explicit model-based method.

The Tier 2 method for biochar amendments is a practice-based approach and does not lead to a fully integrated calculation of SOC stock changes for mineral soils. The main consequence is that the method may not capture the priming of other soil organic matter. Further research is needed to develop a method that does a fully integrated estimation of biochar and other soil organic matter.

Organic Soils

Use the explicit model-based method to estimate uncertainty for C stock losses from the drainage of organic soils (see chapter 8). Uncertainty is assumed to be minor for the management activity data provided by the entity, and therefore the values are assumed to be certain. Uncertainty in the emission factor is provided in table 3-13 of section 3.2.3.1, and is propagated through the calculations using a Monte Carlo simulation. See chapter 8 for more information about the explicit model-based method.

The method for estimation of SOC stock changes for organic soils has an uncertainty associated with emission factors, like the other methods in this section. However, it is limited when estimating the effect of mitigation measures such as water table management. Emission factors are set for each climate region and there are insufficient data to derive scaling factors to adjust the emission factors. Only complete restoration of a wetland with no further drainage can be addressed with the method for mitigation of CO_2 emissions (i.e., it assumes no further emissions of CO_2).

Limitations

Although there is uncertainty in the Tier 2 and 3 methods for mineral and organic soils, there are no known limitations in applying the methods to all croplands and grazing lands in the United States, except for the biochar C method as discussed below. However, it is important to apply the correct method to the land parcel following the directions given in figure 3-3.

The limitation in applying the biochar C method to U.S. cropland and grazing lands is that it is only developed for mineral soils. Further research is needed to expand this method for the estimation of biochar amendments in organic soils (i.e., *Histosols*).

While there is considerable evidence and mechanistic understanding of the influence of land use and management on SOC, less is known about the effect on soil inorganic carbon. Consequently, this set of methods is limited to SOC only. Methods may be added in the future as more studies are conducted and methods are developed to estimate the influence of land use and management on soil inorganic carbon stocks.

3.2.4 Soil Nitrous Oxide

Box 3-7. Method for Estimating Soil Direct N_2O Emissions

- Use the DayCent process-based model for major field crops and grazing lands occurring on most mineral soils. The model simulates the impacts of various management practices (e.g., irrigation, crop and forage type, fertilizer type, and rate) on plant-soil system nitrogen cycling and the processes responsible for N_2O emissions.
- For some crops (e.g., vegetable crops such as lettuce and carrots) and mineral soils (e.g., gravelly), as well as drained organic soils, use the IPCC Tier 1 method (Hergoualc'h et al., 2019) to estimate emissions with scaling factors to address the influence of specific management practices.

Box 3-8. Method for Estimating Soil Indirect N_2O Emissions

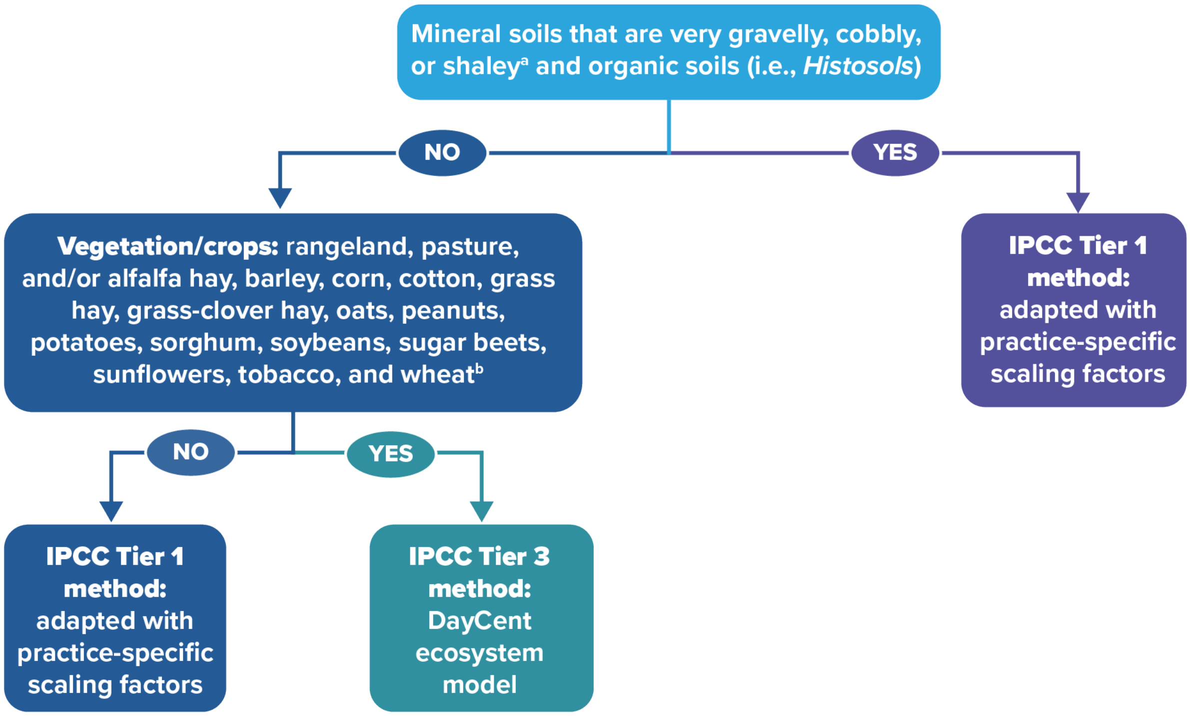
- Use the IPCC Tier 1 method for indirect soil N_2O emissions (Hergoualc'h et al., 2019).
- Use IPCC defaults for estimating the proportion of nitrogen that is subject to leaching, runoff, and volatilization. Inland parcels where the precipitation plus irrigation water input is less than 80 percent of the potential evapotranspiration, nitrogen leaching, and runoff are considered negligible and no indirect N_2O emissions are estimated from leaching and runoff.

3.2.4.1 Description of Method

N_2O is emitted from cropland and grazing land soils both directly and indirectly. Direct emissions are fluxes from cropland or grazing lands where there are nitrogen additions such as mineral fertilization, or management practices that influence nitrogen mineralization from soil organic matter. Indirect emissions occur when reactive nitrogen is volatilized as NH_3 or NO_x or transported via surface runoff or leaching in soluble forms from cropland or grazing lands where nitrogen additions are occurring, or management practices are influencing nitrogen mineralization from soil organic matter. See appendix 3A.3 for the rationale for choosing the following method to estimate emissions.

Direct Emissions

Direct soil N_2O emissions are estimated using either the DayCent process-based model (Tier 3 approach) or a modified IPCC Tier 1 method. Emissions from both methods are scaled for specific management practices that influence N_2O emissions that are not addressed in the Tier 1 or 3 models. figure 3-3 provides a decision tree for choosing the method that is appropriate for the land parcel. In some cases, both methods may need to be used—e.g., if the land parcel has both organic and mineral soils.



[a] Classified as soils whose volume is more than 35 percent gravel, cobbles, or shale.

[b] If other crops are grown in rotation with this set of crops, the IPCC Tier 1 method should be used to estimate emissions. Other crops may be included with Tier 3 method if they are included in the Tier 3 method for future U.S. National GHG Inventories (published annually; most recent version is U.S. EPA, 2020). In addition, USDA may review and potentially approve crops for inclusion in the Tier 3 method if crop production can be simulated with reasonable accuracy using the DayCent model.

Figure 3-3. Decision Tree to Choose the Method for Estimating N_2O Emissions From Mineral and Organic Soils (i.e., Histosols) for the Land Parcel in Equation 3-7

Tier 3 method: Use the DayCent ecosystem model to estimate N_2O emissions (and also soil C stock changes for mineral soils; see section 3.2.3.1), which is consistent with the approach used for the U.S. National GHG Inventory (U.S. EPA, 2020). DayCent estimates emissions based on crop type, soil type, land management, and weather. This approach involves a three-step process in which the first two steps produce an estimate of the initial SOC stocks before the reporting period:

- Run the model to a steady-state condition[16] (e.g., equilibrium) with native vegetation,[17] historical climate data,[18] and the soil physical attributes for the land parcel.
- Simulate a period from the mid-1800s to the most recent year before the first year in the reporting period. The entity can choose the practices that best match the land management for the parcel. In addition, the entity may enter more specific information about the

[16] The goal of the steady-state simulation is to set the state-variables (e.g., amount of C in the soil organic matter pools) in a range that is consistent with environmental conditions at the site.

[17] Broad vegetation types representing the dominant mixture of C_3 and C_4 grasses in grasslands and dominant forest types such as broadleaf deciduous or evergreen needleleaf.

[18] Historical data will depend on the time series, and PRISM has data from 1980 to the present. See section 3.2.3.3.

management of the parcel during the last 30 years of the time series if available, including specific crops planted, tillage practices, fertilization practices, irrigation, and other management activity. Otherwise, the entity can choose from the general management options based on common regional practices (see section 3.2.3.2 for more information). The simulated organic carbon stock at the end of the simulation provides the initial baseline.

- Estimate N_2O emissions during the reporting period based on the management activity for the land parcel and the initial SOC stocks. The management activities for the land parcel, should include crops planted, tillage practices, fertilization practices, irrigation, and other management activity data (see section 3.2.3.2 for more information). Simulations are conducted and outputs for annual N_2O emissions are compiled. Apply the implicit model-based method to estimate uncertainty in the prediction of direct N_2O emissions from the DayCent ecosystem model as discussed in section 3.2.4.4.

Practice-based emission scaling factors, ranging from 0 to 1, are used to adjust the emissions if the land parcel is managed with biochar addition to soils. The biochar[19] scaling factor (S_{bc}) applies only for the first year following application at a minimum rate of 10 Mg/ha. The scaling factor is given a value of 0 if there are repeated applications to the same parcel of land in subsequent years, even if the repeated applications do not occur every year (i.e., no additional scaling). Estimate annual direct soil N_2O emissions based on the DayCent model results and practice-based scaling factor for biochar, using equation 3-15.

Equation 3-15: Tier 3 Annual Direct Soil N_2O Emissions From Mineral Soils

$$N_2O_{direct} = ER_{DayCent} \times (1 + S_{bc}) \times A \times N_2O_{MW} \times N_2O_{GWP}$$

Where:

N_2O_{direct}	=	annual soil N_2O emissions for the land parcel (metric tons CO_2-eq)
$ER_{DayCent}$	=	annual soil N_2O emissions for the land parcel based on DayCent model simulation after applying the implicit model-based uncertainty method (metric tons N_2O-N/ha)
S_{bc}	=	scaling factor for biochar addition, 0 with no addition (dimensionless)
A	=	area of a parcel of land (ha)
N_2O_{MW}	=	ratio of molecular weights of N_2O to N_2O-N, 44/28
N_2O_{GWP}	=	global warming potential for N_2O (metric tons CO_2-eq/metric tons N_2O)

The scaling factor for biochar additions is provided in table 3-17.

Tier 1 method (adapted): This method has been adapted from the IPCC Tier 1 method (Hergoualc'h et al., 2019) with scaling factors to address specific management factors, which are not included in the default Tier 1 method. The IPCC default emission factors vary from 0.2 to 1.6 percent based on nitrogen input type and climate. Multiply these by the appropriate value of nitrogen input to estimate emissions. Use practice-based emission scaling factors ranging from 0 to 1 (see table 3-17) to adjust the emissions for specific management practices associated with fertilizer type, tillage practice, and biochar addition. Specifically, use the scaling factors for fertilizer type to adjust the emissions for slow-release fertilizers (S_{sr}) and nitrification inhibitors (S_{inh}). Use the scaling factor for tillage (S_{till}) to adjust the emissions on land parcels with no-till management. As with the Tier 3 method, a biochar scaling factor (S_{bc}) adjusts the emissions for the first year

[19] Biochars, as defined for these methods, have $H{:}C_{org}$ ratios of < 0.7. See more discussion in section 3.2.3.

following application at a minimum rate of 10 Mg/ha. In the case of repeated applications to the same parcel of land in subsequent years (even if the applications do not occur every year), set the biochar scaling factor (S_{bc}) to a value of 0.

To address drainage of organic soils with this method, multiply the area of drained organic soils by an emission factor. Nitrogen inputs must also be addressed for organic soils, but there is also an additional effect on N_2O emissions from drainage. Organic soils include *Histosols* and soils that have high organic matter content that developed under saturated, anaerobic conditions for at least part of the year, which includes *Histels*, *Historthels*, and *Histoturbels*. The method assumes that there is a significant organic horizon in the soil, so major inputs of nitrogen are from the oxidation of organic matter. If the organic horizon has decomposed and is no longer present in the parcel, the entity does not need to estimate additional emissions associated with the drainage of organic soils.

Equation 3-16 estimates annual direct soil N_2O emissions using the Tier 1 method with practice-based scaling factors.

Equation 3-16: Tier 1 Annual Soil N_2O Emission Rate for Mineral and Organic Soils

$$N_2O_{Direct} = (N_2O_{Input} + N_2O_{OS}) \times N_2O_{MW} \times N_2O_{GWP}$$

Where:

N_2O_{Direct}	=	annual direct soil N_2O emissions for the land parcel (metric tons CO_2-eq)
N_2O_{Input}	=	annual soil N_2O emissions from nitrogen inputs to the land parcel (metric tons N_2O-N)
N_2O_{OS}	=	annual soil N_2O emissions from the drainage of organic soils (metric tons N_2O-N)
N_2O_{MW}	=	ratio of molecular weights of N_2O to N_2O-N = 44/28
N_2O_{GWP}	=	global warming potential for N_2O (metric tons CO_2-eq/metric tons N_2O)

$$N_2O_{Input} = \{[F_{sn} \times EF_{sn} \times (1 + S_{sr}) \times (1 + S_{inh})] + [(F_{on} + F_{cr}) \times EF_{on}] + (F_{prp} \times EF_{prp})\} \times (1 + S_{till}) \times (1 + S_{bc})$$

Where:

N_2O_{Input}	=	annual soil N_2O emissions from nitrogen inputs to the land parcel (metric tons N_2O-N)
F_{sn}	=	synthetic fertilizer nitrogen inputs to the land parcel (metric tons N)
EF_{sn}	=	emission factor for synthetic nitrogen input to soils (metric tons N_2O-N/metric tons N)
S_{sr}	=	scaling factor for slow-release fertilizers, 0 where no effect (dimensionless)
S_{inh}	=	scaling factor for nitrification inhibitors, 0 where no effect (dimensionless)
F_{on}	=	organic fertilizer/manure nitrogen inputs to the land parcel (metric tons N)
F_{cr}	=	crop residue and forage renewal nitrogen inputs to the land parcel (metric tons N)
EF_{on}	=	emission factor for other nitrogen inputs, i.e., organic fertilizer/manure and crop/forage residue nitrogen input to soils (metric tons N_2O-N/metric tons N)

F_{prp}	=	manure nitrogen deposited directly onto the land parcel (i.e., PRP) by livestock (metric tons N)
EF_{prp}	=	emission factor for manure deposited directly onto the land parcel (i.e., PRP) by the livestock (metric tons N_2O-N/metric tons N)
S_{till}	=	scaling factor for no-tillage, 0 except for no-till (dimensionless)
S_{bc}	=	scaling factor for biochar addition—mineral soils only, 0 with no addition or organic soils (dimensionless)

$$N_2O_{OS} = (A_{os} \times EF_{os})/1000$$

Where:

N_2O_{OS}	=	annual soil N_2O emissions from the drainage of organic soils (metric tons N_2O-N)
EF_{os}	=	emission factor for drained organic soils in croplands and grazing lands (kg N_2O-N/ha)
A_{os}	=	area of land parcel with drained organic soils (ha)

The emission and scaling factors for equation 3-15 and equation 3-16 are either defaults provided by IPCC (Drösler et al., 2013; Hergoualc'h et al., 2019) or management practice scaling factors from the published literature or analysis by the authors of this chapter. The factor values and uncertainties are provided in table 3-17.

Table 3-17. IPCC Tier 1 Emission Factors and Practice-Based Scaling Factors for Nitrogen Management Practices With 95-Percent Confidence Intervals

Emission Factor or Scaling Factor for Management Practice	Conditions	Factor (95-Percent Confidence Intervals)	Distribution	Source
Emission factor for synthetic nitrogen input *(EF_{sn})* (metric tons N_2O-N/metric tons N)	Semi-arid/arid climate[a]	0.005 (0.001 to 0.011)	Triangle	Hergoualc'h et al. (2019), i.e., IPCC Tier 1 factors
	Mesic/wet climate[a]	0.016 (0.013 to 0.019)	Triangle	
Slow-release fertilizer use scaling factor *(S_{sr})* (dimensionless)	Semi-arid/arid climate[a]	-0.38 (-0.11 to -0.57)	Normal	See 3A.4
	Mesic/wet climate[a]	-0.20 (-0.08 to -0.30)	Normal	See 3A.4
Nitrification inhibitor use factor *(S_{inh})* (dimensionless)	Semi-arid/arid climate[a]	-0.46 (-0.34 to -0.55)	Normal	See 3A.4
	Mesic/wet climate[a]	-0.33 (-0.24 to -0.42)	Normal	See 3A.4
Emission factor for other nitrogen inputs (organic fertilizer, manure and crop residue) *(EF_{on})* (metric tons N_2O-N/metric tons N)	Semi-arid/arid climate[a]	0.006 (0.001 to 0.011)	Triangle	Hergoualc'h et al. (2019), i.e., IPCC Tier 1 factors
	Mesic/wet climate[a]	0.005 (0.000 to 0.011)	Triangle	

<table>
<tr><th>Emission Factor or Scaling Factor for Management Practice</th><th colspan="2">Conditions</th><th>Factor (95-Percent Confidence Intervals)</th><th>Distribution</th><th>Source</th></tr>
<tr><td rowspan="3">Emission factor for manure nitrogen directly deposited on PRP (EF_{prp}) (metric tons N_2O-N/metric tons N)</td><td rowspan="2">Dairy and beef cattle, buffalo, poultry, and pigs</td><td>Semi-arid/arid climate[a]</td><td>0.002
(0.000 to 0.006)</td><td>Triangle</td><td rowspan="3">Hergoualc'h et al. (2019), i.e., IPCC Tier 1 factors</td></tr>
<tr><td>Mesic/wet climate[a]</td><td>0.006
(0.000 to 0.026)</td><td>Triangle</td></tr>
<tr><td colspan="2">Sheep and other livestock, all climates</td><td>0.003
(0.000 to 0.010)</td><td>Triangle</td></tr>
<tr><td rowspan="2">Emission factor for nitrogen inputs to flooded rice cultivation (EF_{sn} and EF_{on})[b] (metric tons N_2O-N/metric tons N)</td><td colspan="2">Continuous flooding</td><td>0.003
(0.000 to 0.010)</td><td rowspan="2">Triangle</td><td rowspan="2">Hergoualc'h et al. (2019), i.e., IPCC Tier 1 factors</td></tr>
<tr><td colspan="2">Single and multiple drainage</td><td>0.005
(0.000 to 0.006)</td></tr>
<tr><td>Biochar scaling factor (S_{bc}) (dimensionless)</td><td colspan="2">First year application only</td><td>-0.23
(-0.05 to -0.41)</td><td>Normal</td><td>See appendix 3A.4</td></tr>
<tr><td rowspan="4">Tillage scaling factor (S_{till}) (dimensionless)</td><td colspan="2">Semi-arid/arid climate[a] (< 10 years following no-till adoption)</td><td>0.38
(0.04 to 0.72)</td><td>Normal</td><td>van Kessel et al. (2012), Six et al. (2004)</td></tr>
<tr><td colspan="2">Semi-arid/arid climate[a] (≥ 10 years following no-till adoption)</td><td>-0.33
(-0.16 to -0.5)</td><td>Normal</td><td>van Kessel et al. (2012), Six et al. (2004)</td></tr>
<tr><td colspan="2">Mesic/wet climate[a] (< 10 years following no-till adoption)</td><td>-0.015
(-0.16 to 0.16)</td><td>Normal</td><td>van Kessel et al. (2012), Six et al. (2004)</td></tr>
<tr><td colspan="2">Mesic/wet climate[a] (≥ 10 years following no-till adoption)</td><td>-0.09
(-0.19 to -0.01)</td><td>Normal</td><td>van Kessel et al. (2012), Six et al. (2004)</td></tr>
<tr><td rowspan="2">Emission factor for drained cropland soils (EF_{OS}) (kg N_2O-N/ha)</td><td colspan="2">Temperate</td><td>13
(8.2 to 18)</td><td>Triangle</td><td rowspan="6">Drösler et al. (2013), i.e., IPCC Tier 1 factors</td></tr>
<tr><td colspan="2">Subtropical/tropical</td><td>5.0
(2.3 to 7.7)</td><td>Triangle</td></tr>
<tr><td rowspan="4">Emission factor for drained grazing land soils (EF_{OS}) (kg N_2O-N/ha)</td><td colspan="2">Temperate, nutrient poor</td><td>4.3
(1.9 to 6.8)</td><td>Triangle</td></tr>
<tr><td colspan="2">Temperate, nutrient rich, deep drainage</td><td>8.2
(4.9 to 11)</td><td>Triangle</td></tr>
<tr><td colspan="2">Temperate, nutrient rich, shallow drainage</td><td>1.6
(0.56 to 2.7)</td><td>Triangle</td></tr>
<tr><td colspan="2">Subtropical/tropical</td><td>5.0
(2.3 to 7.7)</td><td>Triangle</td></tr>
</table>

The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

[a] Wet/mesic climates occur in temperate and boreal regions where the ratio of mean annual precipitation to potential evapotranspiration is greater than 0.8 and all other climates are considered arid/semi-arid. Wet/mesic climates in

subtropical/tropical regions occur where the mean annual precipitation is greater than 1,000 mm and other climates are considered semi-arid or arid.

[b] The EF_{sn} and EF_{on} for flooded rice cultivation differ from other crops due to the anaerobic conditions under which flooded rice is produced.

The reporting entity provides the amount of synthetic fertilizer and other organic nitrogen inputs; use of no-till, biochar amendments, nitrification inhibitors in fertilizers, and slow-release fertilizers with polymer coatings; and the area of drained organic soils (see section 3.2.4.2 for a complete list of requirements). Estimate the amount of manure nitrogen deposited directly onto land parcels using methods in the livestock methods in chapter 4. Estimate crop residue nitrogen and forage renewal nitrogen inputs using equation 3-17. Note that crop residue nitrogen input is only estimated for herbaceous crops, and that forage nitrogen inputs are only estimated in years when the grazing land is cleared (with practices such as tillage or herbicides) and replanted with forages.

Equation 3-17: Annual Amount of Crop and Forage Residue Nitrogen Input to the Soil

$$F_{cr} = CRN_a + CRN_b$$

Where:

F_{cr}	=	residue nitrogen inputs to the land parcel from annual crops and litter/dead biomass produced during grazing land renewal (metric tons N)
CRN_a	=	aboveground crop and forage renewal residue inputs to the land parcel (metric tons N)
CRN_b	=	belowground crop and forage renewal residue inputs to the land parcel (metric tons N)

$$CRN_b = CB_a \times (1 + R) \times N_b$$

Where:

CRN_b	=	belowground crop and forage renewal residue inputs to the land parcel (metric tons N)
CB_a	=	aboveground crop and forage biomass in dry matter units (metric tons of dry matter)
R	=	aboveground biomass to belowground biomass (root-to-shoot) ratio (metric tons belowground dry matter/metric tons aboveground dry matter)
N_b	=	N content in the belowground residue (metric tons N/metric tons dry matter)

$$CRN_a = [(CB_a - (Y \times A)) \times N_a] \times (1 - R_m)$$

Where:

CRN_a	=	aboveground crop and forage renewal residue inputs to the land parcel (metric tons N)
CB_a	=	aboveground crop and forage biomass in dry matter units (metric tons of dry matter)
Y	=	fresh weight of crop harvest yield or peak grazing land forage amount (metric tons yield/ha)
A	=	area of a parcel of land (ha)
N_a	=	N content in the aboveground residue (metric tons N/metric tons dry matter)

R_m = proportion of crop or forage residue removed by burning, grazing, or harvesting residues (metric tons dry matter removed/metric tons dry matter produced)

$$CB_a = (Y \div HI) \times A \times DM$$

Where:

CB_a = aboveground crop and forage biomass in dry matter units (metric tons of dry matter)

Y = fresh weight of crop harvest yield or peak grazing land forage amount (metric tons yield/ha)

HI = harvest index: ratio of crop yield or forage removal to total aboveground biomass (metric tons biomass/metric tons yield)

A = area of a parcel of land (ha)

DM = dry matter content of harvested crop biomass or forage (metric tons dry matter/metric tons biomass)

Crop yield data and the grazing land forage amount should be provided by the entity. The amount of forage should be approximated based on the peak forage amount using methods in section 3.2.1.2. The forage renewal nitrogen inputs (F_{cr}) should be 0 for land parcels with grazing lands that are not renewed during the reporting year (i.e., cleared with practices such as tillage or herbicides, then replanted with forages). The harvest index, dry matter contents, and root-to-shoot ratios can be found in table 3-3. The nitrogen content of the crop and forage residues is provided in table 3-18.

Table 3-18. Crop and Forage Nitrogen Content With 95-Percent Confidence Intervals in Parentheses

Crop	Nitrogen Content of Aboveground Residues (Metric Tons N/Metric Tons Dry Matter)	Nitrogen Content of Belowground Residues (Metric Tons N/Metric Tons Dry Matter)
Barley	0.007 (±0.005)	0.014 (±0.011)
Beans	0.008 (±0.006)	0.008 (±0.006)
Corn grain/silage	0.006 (±0.005)	0.007 (±0.005)
Cotton	0.012 (±0.009)	0.007 (±0.005)
Millet	0.006 (±0.005)	0.009 (±0.007)
Oats	0.007 (±0.005)	0.008 (±0.006)
Peanuts	0.016 (±0.012)	0.014 (±0.011)
Potatoes	0.019 (±0.014)	0.014 (±0.011)
Rice	0.007 (±0.005)	0.009 (±0.007)
Rye	0.005 (±0.004)	0.011 (±0.008)
Sorghum grain/silage	0.007 (±0.005)	0.006 (±0.005)
Soybean	0.008 (±0.006)	0.008 (±0.006)
Sugar beets	0.019 (±0.014)	0.014 (±0.011)
Sugarcane	0.007 (±0.005)	0.005 (±0.004)
Sunflower	0.006 (±0.005)	0.009 (±0.007)
Tobacco	0.008 (±0.006)	0.018 (±0.014)
Spring wheat	0.006 (±0.005)	0.009 (±0.007)

Crop	Nitrogen Content of Aboveground Residues (Metric Tons N/Metric Tons Dry Matter)	Nitrogen Content of Belowground Residues (Metric Tons N/Metric Tons Dry Matter)
Winter wheat	0.006 (±0.005)	0.009 (±0.007)
Other grain crops	0.006 (±0.005)	0.009 (±0.007)
Other crops	0.006 (±0.005)	0.009 (±0.007)
Alfalfa hay	0.027 (±0.020)	0.019 (±0.014)
Nonlegume hay	0.015 (±0.011)	0.012 (±0.009)
Nitrogen-fixing forages	0.027 (±0.020)	0.022 (±0.017)
Perennial grass forages	0.015 (±0.011)	0.012 (±0.009)
Other forages (i.e., not perennial grass or nitrogen-fixing)	0.015 (±0.011)	0.012 (±0.009)
Grass and nitrogen-fixing (e.g., clover) forage mixtures	0.025 (±0.019)	0.016 (±0.012)

Sources: Hergoualc'h et al., 2019, i.e., IPCC Tier 1 factors, with additional values from U.S. EPA, 2020.

The 95-percent confidence intervals are based on a normal distribution that can be used to quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

Note: The Tier 1 method does not include crop residue N input from woody crops.

Indirect Emissions

The method to estimate indirect N_2O emissions for mineral soils has been adopted from the approach developed by IPCC (Hergoualc'h et al., 2019). Using equation 3-18, estimate the total indirect N_2O emissions associated with volatilization, leaching, and runoff from a land parcel.

Equation 3-18: Total Annual Indirect Soil N_2O Emissions from Mineral Soils

$$N_2O_{indirect} = (N_2O_{vol} + N_2O_{leach}) \times N_2O_{MW} \times N_2O_{GWP}$$

Where:

$N_2O_{indirect}$	=	annual indirect soil N_2O emissions (metric tons CO_2-eq)
N_2O_{vol}	=	N_2O emitted by the ecosystem receiving volatilized nitrogen (metric tons N_2O-N)
N_2O_{leach}	=	N_2O emitted by ecosystem receiving leached and runoff nitrogen (metric tons N_2O-N)
N_2O_{MW}	=	ratio of molecular weights of N_2O to N_2O-N = 44/28 (metric tons N_2O/metric tons N_2O-N)
N_2O_{GWP}	=	global warming potential for N_2O (metric tons CO_2-eq/metric tons N_2O)

Use equation 3-19 to estimate the indirect emissions associated with the volatilization of nitrogen-based gases from a land parcel.

Equation 3-19: Annual Indirect Soil N_2O Emissions From Mineral Soils—Volatilization

$$N_2O_{vol} = \{(F_{SN} \times FR_{SN}) + [(F_{ON} + F_{PRP}) \times FR_{ON}]\} \times EF_{vol}$$

Where:

N_2O_{vol}	=	annual indirect soil N_2O emitted by the ecosystem receiving volatilized nitrogen (metric tons N_2O-N)
F_{SN}	=	synthetic nitrogen fertilizer applied (metric tons N)
FR_{SN}	=	fraction of synthetic nitrogen (NSN) that volatilizes as NH_3 and NO_x [metric tons N/metric tons nitrogen in synthetic fertilizer]
F_{ON}	=	nitrogen fertilizer applied of organic origin including manure, sewage sludge, compost, and other organic amendments (metric tons N)
F_{PRP}	=	manure nitrogen deposited directly onto the land parcel (i.e., PRP) by livestock (metric tons N)
FR_{ON}	=	fraction or proportion of F_{ON} that volatilizes as NH_3 and NO_x (metric tons N/metric tons nitrogen in organic fertilizer)
EF_{vol}	=	emission factor for volatilized nitrogen or proportion of nitrogen volatilized as NH_3 and NO_x that is transformed to N_2O in receiving ecosystem (metric tons N_2O-N/metric tons N)

Use equation 3-20 to estimate the indirect emissions associated with leaching and runoff of organic and inorganic forms of nitrogen from a land parcel.

Equation 3-20: Tier 1 Annual Indirect Soil N_2O Emissions From Mineral Soils—Leaching and Runoff

$$N_2O_{leach} = (N_i \times FR_{leach}) \times EF_{leach}$$

Where:

N_2O_{leach}	=	annual indirect soil N_2O emitted by ecosystem receiving leached and runoff nitrogen (metric tons N_2O-N)
N_i	=	nitrogen inputs, including mineral fertilizer, organic amendments, PRP manure nitrogen, and residues (metric tons N)
FR_{leach}	=	fraction of nitrogen inputs (N_i) that is leached or runs off the land parcel (metric tons N/metric tons N in nitrogen inputs)
EF_{leach}	=	proportion of leached and runoff nitrogen that is transformed to N_2O in the receiving ecosystem (metric tons N_2O-N/metric tons N)

Emission factors and fractions for volatilization ($N_{volatilized}$), leaching, and runoff ($N_{leached/runoff}$) are provided in table 3-19. The fraction of nitrogen that is leached from a profile will vary depending on the level of precipitation and irrigation water applied to the field, among other properties like soil texture, pH and temperature. Inland parcels (i.e., fields) where the precipitation and irrigation water inputs are less than 80 percent of the potential evapotranspiration, leaching, and runoff are considered negligible and no indirect N_2O emissions should be estimated (U.S. EPA, 2020). IPCC default fractions are used for EF_{leach} and FR_{leach} where no cover crops are present. Where winter cover crops precede the cash crop, FR_{leach} is further adjusted to account for cover crop effects on nitrate leaching. Note that CO_2 emissions from urea are addressed separately in section 3.2.9.

Table 3-19. Tier 1 Emission Factors for Estimating Indirect Soil N_2O Emissions With 95-Percent Confidence Intervals

Emission Factors	Condition	Factor (95-Percent Confidence Intervals)	Units	Distribution	Source
Fraction of synthetic nitrogen (N_{SN}) that volatilizes as NH_3 and NO_x	Urea fertilizer	0.15 (0.03 to 0.43)	Metric tons $N_{volatilized}$/ metric ton F_{SN}	Triangle	Hergoualc'h et al. (2019), i.e., IPCC Tier 1 factors
	Ammonium-based fertilizer	0.08 (0.02 to 0.3)	Metric tons $N_{volatilized}$/ metric ton F_{SN}	Triangle	
	Nitrate-based fertilizer	0.01 (0.00 to 0.02)	Metric tons $N_{volatilized}$/ metric ton F_{SN}	Triangle	
	Ammonium-nitrate-based fertilizer	0.05 (0.00 to 0.2)	Metric tons $N_{volatilized}$/ metric ton F_{SN}	Triangle	
Fraction of nitrogen in organic amendments (excluding crop residues) and PRP nitrogen ($F_{ON,PRP}$) that volatilizes as NH_3 and NO_x	n/a	0.21 (0.00 to 0.31)	Metric tons $N_{volatilized}$/ metric ton F_{ON}, F_{PRP}	Triangle	
Indirect soil N_2O emission factor for volatilized nitrogen losses	Wet/mesic climate[a]	0.014 (0.011 to 0.017)	Metric tons N_2O-N/metric ton $N_{volatilized}$	Triangle	
	Semi-arid/arid climate[a]	0.005 (0.000 to 0.011)	Metric tons N_2O-N/metric ton $N_{volatilized}$	Triangle	
Fraction of nitrogen inputs (mineral fertilizer nitrogen, organic nitrogen, crop residue nitrogen, and PRP nitrogen) to the site that leach or run off in water flows	Without cover crops	0.24 (0.01 to 0.73)	Metric tons $N_{leached/runoff}$/ metric ton N_i	Triangle	
	With leguminous cover crop	0.18 (0.14 to 0.26)	Metric tons $N_{leached/runoff}$/ metric ton N_i	Triangle	
	With non-leguminous cover crop	0.09 (0.06 to 0.15)	Metric tons $N_{leached/runoff}$/ metric ton N_i	Triangle	
Indirect soil N_2O emission factor for leached and runoff losses of nitrogen	n/a	0.011 (0.000 to 0.02)	Metric tons N_2O-N/ metric ton $N_{leached/runoff}$	Triangle	

Probability density functions have a triangular distribution that can be used to propagate error through the analysis and quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

[a] Wet/mesic climates occur in temperate regions where the ratio of mean annual precipitation to potential evapotranspiration ratio is greater than 0.8 and all other climates are considered arid/semi-arid. Wet/mesic climates in subtropical/tropical regions occur where the mean annual precipitation is greater than 1,000 mm and other climates are considered semi-arid or arid.

Box 3-9. Method for Projecting Soil N_2O Emissions

For estimation of future direct and indirect soil N_2O emissions, the methods described in this section can be applied using the DayCent model and Tier 1 approach in combination with expected management practices. For DayCent simulations, the previous 10 years of weather will be repeated for the projections. The equations should be applied in a business-as-usual scenario and the mitigation scenario: the difference in emissions between the two scenarios is an estimate of the technical mitigation potential for the land parcel. Projections should only be used for planning; for reporting, emissions from the land parcel should be estimated with the actual weather and management practices. Other considerations—e.g., cost for adopting a new practice, issues surrounding permanence and leakage—are not addressed with these methods but may also influence the amount of GHG mitigation.

3.2.4.2 Activity Data

Overview of Requirements

Activity data requirements are provided by the reporting entity. Requirements include information on soil and nitrogen management practices that influence N_2O emissions.

Croplands

Some activity data requirements for croplands are common to both the Tier 3 and Tier 1 methods:

- Area of the land parcel (i.e., field)
- Crop types and rotation sequence
- Residue management, including proportion harvested, burned, grazed, or left in the field
- Mineral fertilizer type (including enhanced-efficiency fertilizers with nitrification inhibitors or polymer-coated fertilizers) and application rate
- Organic amendment type (e.g., manure and composted manure by livestock type, other organic fertilizers), and application rate
- Tillage implements and number of passes in each operation[20]
- Irrigation use on land parcel
- Amount of biochar application to the land parcel
- Whether biochar has previously been applied to this parcel of land
- Cover crop types

The additional activity data needed for the Tier 3 method using the DayCent process-based model[21] include:

- Planting and harvesting dates
- Mineral fertilizer application method and timing of application(s)

[20] Use this information to determine tillage intensity (i.e., intensive till, reduced till, and no-till), using the classification applied in the U.S. National GHG Inventory. See section 3.2.3.2 for more information about the tillage classification.

[21] The data requirements for the Tier 3 method are to estimate SOC stock changes and soil N_2O emissions (see section 3.2.3.2).

- Organic amendment application method and timing of application(s)
- Timing of tillage operations
- Months of the year when the land parcel is irrigated
- Use of drainage practices in mineral soils and depth of drainage (common in hydric soils)
- Cover crop planting and harvesting dates, and termination method

The additional information needed for the Tier 1 method includes:

- Crop harvest yields for annual crops
- Area of drained organic soils

Grazing Lands

As with croplands, some activity data requirements for grazing lands are common to both the Tier 3 and Tier 1 methods:

- Area of the land parcel (i.e., field)
- Forage type (perennial grass such as cool or warm season grasses, legume, or mixed grass-legume nitrogen-fixing species)
- Animal type and stocking rates
- Mineral fertilizer type (including enhanced-efficiency fertilizers with nitrification inhibitors or polymer-coated fertilizers) and application rate
- Organic amendment type (e.g., manure and composted manure by livestock type, other organic fertilizers), and application rate
- Use of irrigation on the land parcel (yes/no)
- Residue management, including proportion harvested, burned, grazed, or left in the field
- Renewal of the grazing land (yes/no)
- Amount of biochar application to the land parcel
- Whether biochar has previously been applied to this parcel of land

The additional activity data for grazing lands needed for the Tier 3 method using the DayCent process-based model include:

- Months of the year with grazing
- Grazing method (continuous, rotational, or other types)
- Use of drainage practices and depth of drainage (e.g., drainage to improve grazing conditions in hydric soils)
- Tillage implements and timing of tillage operations, and/or timing of herbicide applications for renewal of forage grazing land, in addition to the timing and type of forage that is replanted or naturally regenerates on the land parcel
- Months of the year when the land parcel is irrigated

The additional grazing lands information needed for the Tier 1 method includes:

- Peak forage production before renewal of forage on grazing land

- Area of drained organic soils

Additional Notes on Activity Data Requirements

Crop yields are provided by the reporting entity for the crop system, as are peak forage amounts for grazing systems. In some years, the entity may not harvest the crop due to drought, pest outbreaks, or other reasons for crop failure. Similarly, forage production may decline to near zero in some years due to droughts. In those cases, the entity should provide the average crop yield or peak forage production in the past 5 years, along with an approximate percentage of crop or forage growth that occurred before crop failure or forage decline. To estimate the yield, the entity should multiply the average crop yield or peak forage production by the percentage of crop or forage growth obtained before failure or forage decline.

The entity provides the amount of synthetic fertilizer, but to calculate the amount of synthetic fertilizer nitrogen applied to soils, the nitrogen contents of the fertilizers are also needed. Table 3-20 provides nitrogen content information for common types of synthetic fertilizers. The entity will need to provide the nitrogen content for any type of synthetic fertilizer that is not listed in the table.

Table 3-20. Nitrogen Fraction of Common Synthetic Fertilizers (Percent by Weight)

Synthetic Fertilizer	% N
Ammonium nitrate (NH_4NO_3)	33.5
Ammonium nitrate limestone	20.5
Ammonium sulfate	20.75
Anhydrous ammonia	82
Aqua ammonia	22.5
Calcium cyanamide ($CaCN_2$)	21
Calcium ammonia nitrate	27.0
Diammonium phosphate	18
Monoammonium phosphate	11
Potassium nitrate (KNO_3)	13
Sodium nitrate ($NaNO_3$)	16
Urea [$CO(NH_2)_2$]	45

Source: Nebraska Department of Agriculture, n.d.

These values are assumed to have no significant uncertainty for error propagation in an uncertainty analysis.

Manure amendments require information on both the livestock type and the carbon and nitrogen content of organic inputs. Nitrogen and carbon fractions for common organic fertilizers are provided in table 3-16. In contrast, the entity only needs to provide the type of livestock on grazing lands where the manure is not managed after excretion onto the land, referred to as PRP manure. Use the methods in chapter 4 to estimate the amount of PRP manure nitrogen; assume a split with 50 percent of the nitrogen in urine and the other 50 percent of the nitrogen in solids. Additional notes on the activity data requirements for the Tier 3 method can be found in section 3.2.3.2.

3.2.4.3 Ancillary Data

Ancillary data for the Tier 3 method include historical weather data and soil characteristics. Weather data are based on national datasets such as PRISM (PRISM Climate Group, 2018). Soil characteristics are based on national datasets such as SSURGO (Soil Survey Staff, 2023). The Tier 1 method needs information on the climate based on the IPCC Climate Classification (Reddy et al., 2019), which an entity can derive by estimating mean annual temperature, precipitation, and potential evapotranspiration data from the PRISM data.

3.2.4.4 Limitations and Uncertainty

Direct Emissions

Tier 3 method: Use the implicit model-based method to estimate uncertainty for direct soil N_2O based on the Tier 3 method (see chapter 8). Uncertainty in the Tier 3 method is associated with the DayCent ecosystem model and includes imprecision and bias in the process-based model structure and parameters. Uncertainty is quantified with an empirically based approach, as used in the U.S. National GHG Inventory (Ogle et al., 2007; U.S. EPA, 2020). The method combines modeling and measurements to provide an estimate and uncertainty in direct soil N_2O emissions for entity-scale reporting, similar to soil C. Measurements of soil N_2O emissions may be based on a national soil monitoring network, or agricultural experiments to inform model uncertainty (see U.S. EPA, 2020, for examples associated with the DayCent ecosystem model).

Uncertainty is assumed to be minor for the management activity data provided by the entity, and therefore the values are assumed to be certain. Uncertainties associated with model structure and parameters are quantified using an empirical method, as discussed above. The empirical method is based on fitting a linear mixed-effect model that is given in equation 3-21 for croplands and a linear model that is given in equation 3-22 for grazing lands, along with the covariance matrices for the fixed effects.[22] This model is applied M number of times to produce replicates of direct soil N_2O emissions that can be used to compute the median and 95-percent prediction interval. Note that the same set of random draws, i.e., M random draws, for fixed effects and the random effect for the site are used in the calculation of direct soil N_2O emissions in each year of the time series for a land parcel. In contrast, the M replicates of the residual error are redrawn in each year of the time series for a land parcel. See chapter 8 for more information about how to propagate uncertainty using the implicit model-based method.

Equation 3-21: Empirical Uncertainty Model for Quantifying Uncertainty in the Tier 3 Method for Direct Soil N_2O Emissions in Croplands

$$\begin{aligned} ER_{DayCent} = \exp\{&0.5693 + (0.3577 \times (\ln N_2O_{DayCent} \div 365)) + (0.3373 \times Corn) \\ &+ (-0.2242 \times SF) + (0.2537 \times (\ln N_2O_{DayCent} \div 365) \times SF) + b^{(r)}\} \div 10^6 \times 365 \end{aligned}$$

Where:

$ER_{DayCent}$	=	annual soil N_2O emissions for land parcel based on DayCent model simulation after applying the implicit model-based uncertainty method (metric tons N_2O-N/ha)
$\ln N_2O_{DayCent}$	=	natural log of the predicted annual direct N_2O emissions from the DayCent ecosystem model (grams N_2O-N/ha)
$Corn$	=	assign a value of 1 if the crop is corn, and a value of 0 if the crop is not corn (dimensionless)

[22] The empirical models may be revised if the structure and/or parameterization of the DayCent ecosystem model is modified for the U.S. National GHG Inventory to ensure that entity-scale reporting is consistent with national inventory methods.

SF	=	assign a value of 1 if synthetic fertilizer is applied, and a value of 0 if synthetic fertilizer is not applied (dimensionless)
$b^{(r)}$	=	sum of the random effect associated with the site, site within year and residual error from the linear mixed effect model. The random effects and residue error are drawn from normal distributions with a mean of 0 and the following standard deviations, site = 0.8002, site within year = 0.5921 and residual error = 0.4621
10^6	=	conversion from grams N_2O-N/ha to metric tons N_2O-N/ha,
365	=	conversion for annual estimate (days/year)

The implicit model-based method also requires the following covariance matrix:

	Intercept	**ln $N2O_{DayCent}$**	**Corn**	**SF**	**ln $N_2O_{DayCent} \times SF$**
Intercept	0.016526	-0.00188	-0.00135	-0.0016	0.001167
ln $N_2O_{DayCent}$	-0.00188	0.001751	-0.00023	0.000679	-0.00113
Corn	-0.00135	-0.00023	0.006657	-0.0008	0.00000776
SF	-0.0016	0.000679	-0.0008	0.00742	-0.00312
ln $N_2O_{DayCent} \times SF$	0.001167	-0.00113	0.00000776	-0.00312	0.002111

Equation 3-22. Empirical Uncertainty Model for Quantifying Uncertainty in the Tier 3 Method for Direct Soil N_2O Emissions in Grazing Lands

$$ER_{DayCent} = \exp\{0.4947 + (0.5690 \times (\ln N_2O_{DayCent} \div 365)) + b^{(r)}\} \div 10^6 \times 365$$

Where:

$ER_{DayCent}$	=	annual soil N_2O emissions for land parcel based on DayCent model simulation after applying the implicit model-based uncertainty method (annual metric tons N_2O-N/ha)
$\ln N_2O_{DayCent}$	=	natural log of the predicted annual direct N_2O emissions from the DayCent ecosystem model (g N_2O-N/ha)
$b^{(r)}$	=	residual error from the linear model. The residual error is drawn from a normal distribution with a mean of 0 and a standard deviation of 0.8292.
106	=	conversion from grams N_2O-N/ha to metric tons N_2O-N/ha
365	=	conversion for annual estimate (days/year)

The implicit model-based method also requires the following covariance matrix:

	Intercept	**ln $N_2O_{DayCent}$**
Intercept	0.015942	-0.00724
ln $N2O_{DayCent}$	-0.00724	0.006458

To reduce uncertainty, annual emissions can be aggregated across land parcels by summing N_2O emissions within iterations in the Monte Carlo analysis across entities, and then extracting the median and constructing a 95-percent prediction interval from the aggregated results (see box 8-2 in chapter 8). A similar process can also be used to aggregate annual estimates of N_2O emissions to produce results for multiple years (e.g., change over 5 or 10 years). Uncertainties are larger at finer spatial and temporal scales due to the random effect for site and residual error that is reduced as the calculations incorporate emissions from more land parcels and/or years. Aggregation is a way to manage uncertainty and limit the risk associated with programs that include sequestration of N_2O emissions in agricultural soils as a mitigation pathway (see Ogle et al., 2010, for uncertainty at different scales of aggregation in which uncertainties can be over 100 percent at the entity scale, but significantly reduced with aggregation of farms and ranches to larger spatial scales and aggregating annual data across years).

One of the key sources of uncertainty is limited observations of N_2O emissions that will not allow fluxes for a particular location or time to be predicted precisely. Nevertheless, while it may be decades before annual rates of N_2O emissions from a specific field can be estimated with high certainty and for low cost, average estimates for similar cropping systems and landscapes will converge as estimates aggregate to larger areas.

The key uncertainties in this method are misspecification of the model processes in the DayCent ecosystem model and interactions among management practices that may affect the fundamental processes driving N_2O emissions—e.g., nitrification, denitrification, and gas diffusion. In addition, there is uncertainty due to limited measurement data for evaluating errors in the parameters and structure of DayCent using the empirically based method.

Tier 1 method: Use the explicit model-based method to estimate uncertainty for the Tier 1 method (see chapter 8). Uncertainty is assumed to be minor for the management activity data provided by the entity, and therefore the values are assumed to be certain. Uncertainties in emission factors are provided in section 3.2.4.1, and are propagated through the calculations using a Monte Carlo simulation. Table 3-17 provides the uncertainty for the model parameters associated with the Tier 1 method, including emission factors and scaling factors. Table 3-3 and table 3-18 provide the uncertainty for residue nitrogen calculations. See chapter 8 for more information about the explicit model-based method.

There are additional uncertainties in this method due to a lack of inference about how different management practices affect fluxes across regions and cropping systems, particularly at subnational scales. These limitations contribute to uncertainty in the Tier 1 factors produced by IPCC.

Indirect Emissions

Use the explicit model-based method to estimate uncertainty for the Tier 1 method (see chapter 8). Uncertainty is assumed to be minor for the management activity data provided by the entity, and therefore the values are assumed to be certain. Uncertainties in parameters and factors are provided in section 3.2.4.1, and are propagated through the calculations using a Monte Carlo simulation. Table 3-19 provides the uncertainty for the emission factors and scaling factors. Table 3-3 and table 3-18 provide uncertainty for residue nitrogen calculations. See chapter 8 for more information about the explicit model-based method.

Limitations

Although there is uncertainty in the Tier 1 and 3 methods, there are no known limitations in applying the methods to all croplands and grazing lands in the United States. However, it is important to apply the correct method to the land parcel following the directions given in figure 3-3.

3.2.5 Methane Flux for Nonflooded Soils

Box 3-10. Method for Estimating CH_4 Flux for Nonflooded Soils

- Net CH_4 uptake occurs in nonflooded soils that are used for crop production or grazing land (except for drained organic soils, which can be neutral or a net source).
- Estimation of CH_4 flux for nonflooded mineral soils in cropland and grazing lands is based on CH_4 flux in natural vegetation—whether grassland or forest—attenuated by current cropland or grazing land use practices.
- Estimation of CH_4 flux for drained organic soils is based on CH_4 flux under cropland and grazing land management.
- Methane emissions from nonflooded mineral soils are not addressed by IPCC and are not included in the U.S. National GHG Inventory. The Tier 3 method incorporates entity-specific management data for the land parcel to estimate the CH_4 flux.

3.2.5.1 Description of Method

This method provides an estimate of CH_4 flux for nonflooded soils in croplands and grazing lands. Methane is produced in soils through methanogenesis, which occurs under anaerobic conditions; it is consumed in soils through methanotrophy, which is the dominant process under aerobic conditions. In most nonflooded soils under cropland or grazing land management, there will be a net uptake of CH_4 although the rate will vary depending on the land use (Del Grosso et al., 2000; McDaniel et al., 2019; Mosier et al., 1991; Robertson et al., 2000; Smith et al., 2000). However, wetlands with organic soils that are drained and converted into cropland or grazing land may have no net flux or possibly a net emission of CH_4 to the atmosphere (Drösler et al., 2013; Tan et al., 2020).

Mineral Soils

The calculation for nonflooded mineral soils is based on average CH_4 uptake in soils with natural vegetation—whether grassland or forest—attenuated by current land use (see appendix 3A.6.1 for rationale). Management factors determine the amount of attenuation for the base rates. Use equation 3-23 to estimate the annual amount of CH_4 uptake for nonflooded mineral soils in a land parcel. The factors to estimate CH_4 flux for nonflooded mineral soils are provided in table 3-21.

Equation 3-23: Annual CH_4 Flux in Nonflooded Mineral Soils

$$CH_{4_{nfms}} = (CH_{4_b} \times MF) \times A \times CH_{4_{GWP}}$$

Where:

CH_{4nfms}	=	annual CH_4 flux for nonflooded mineral soils (metric tons CO_2-eq)
CH_{4b}	=	base annual CH_4 flux for mineral soils with natural vegetation (metric tons CH_4/ha)
MF	=	management factor for cropland and grazing land on mineral soils (dimensionless)
A	=	area of the land parcel (ha)
CH_{4GWP}	=	global warming potential for CH_4 (metric tons CO_2-eq/metric tons CH_4)

Drained Organic Soils

The calculation for nonflooded croplands and grazing lands that occur on drained organic soils is based on an average CH_4 flux rate, i.e., emission factor. Use equation 3-24 to estimate the annual CH_4 flux for drained organic soils in a land parcel.

Equation 3-24: Annual CH_4 Flux for Drained Organic Soils

$$CH_{4_{dos}} = CH_{4_{dw}} \times A \times CH_{4_{GWP}}$$

Where:

CH_{4dos}	=	annual CH_4 flux for drained organic soils (metric tons CO_2-eq)
CH_{4dw}	=	CH_4 emission factor for drained organic soils (metric tons CH_4/ha)
A	=	area of the land parcel (ha)
CH_{4GWP}	=	global warming potential for CH_4 (metric tons CO_2-eq/metric tons CH_4)

Table 3-21 provides the factors to estimate CH_4 flux for nonflooded soils.

Table 3-21. Factors and 95-Percent Confidence Intervals for Estimating CH_4 Flux

Parameter	Natural Vegetation	Current Land Use	Factor	95-Percent Confidence Interval	Data Source
Base annual CH_4 flux for mineral soils with natural vegetation *(CH_{4b})* (metric tons CH_4/ha)	Grassland[a]	n/a	-0.0024	±0.0048	See 3A.6.2
	Forest	n/a	-0.0028	±0.0046	See 3A.6.2
Management factor for cropland and grazing land on mineral soils *(MF)* (dimensionless)	Grassland[a]	Annual cropland	0.34	±1.1138	See 3A.6.2
	Forest	Annual cropland	0.32	±0.8220	
	Grassland[a]/forest	Perennial cropland	1	n/a	
CH_4 emission factor for drained organic soils *(CH_{4dw})* (kg CH_4/ha)	Wetland (i.e., organic soil)	Cropland	0	-2.8 to 2.8	Drösler et al. (2013), i.e., IPCC Tier 1 factors
		Grazing land with deep drainage[b]	16	2.4 to 29	
		Grazing land with shallow drainage[b]	39	-2.9 to 81	

The uncertainty is a 95-percent confidence interval with a probability density function that has a normal distribution. These probability density functions can be used to quantify uncertainty in the annual emissions. Factors with "n/a" indicate that uncertainty is not applicable because the uncertainty is already incorporated into the base annual CH_4 flux.

Note: even though the most probable values from the probability distribution functions imply a net gain of CH_4 in mineral soils and a net loss of CH_4 from organic soils, there are large uncertainties in several of these factors. Consequently, there is some probability of a net loss of CH_4 from mineral soils and a net uptake of CH_4 in drained organic soils. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

[a] Grassland includes both native rangelands and pastures for this method. There is no significant difference in the CH_4 flux between pasture and native grasslands (appendix 3A.6.2).

[b] Assume shallow drainage if the depth of drainage if unknown.

3.2.5.2 Activity Data

This method requires current land use and type of natural vegetation. The entity will need to identify the current land use as either cropland or grazing land. If the area is a drained wetland that has been converted into grazing land, the entity will also need to identify if the land has deep or shallow drainage. The entity may identify the natural vegetation if known or use the reference ecological site from the NRCS ecological site descriptions (USDA, 2017), identifying if the parcel would be grassland or forest in the reference condition using the NRCS Web Soil Survey (https://websoilsurvey.nrcs.usda.gov/app/HomePage.htm).[23]

3.2.5.3 Limitations and Uncertainty

Use the explicit model-based method to estimate uncertainty for the methane flux in nonflooded soils (see chapter 8). Uncertainty is assumed to be minor for the management activity data provided by the entity, and therefore the values are assumed to be certain. Uncertainties in base flux rates, management factors, and emission factors are provided in table 3-21 of section 3.2.5.1, and are propagated through the calculations using a Monte Carlo simulation. See chapter 8 for more information about the explicit model-based method.

Major sources of uncertainty for the CH_4 flux method include the following:

- Lack of knowledge about the natural vegetation.
- Uncertainties associated with estimating base CH_4 flux rates for natural vegetation (CH_{4b} in equation 3-20) or drained organic soils (CH_{4dw} in equation 3-21).
- Uncertainty associated with the management factors associated with attenuation of base flux rates for mineral soils, particularly for perennial cropland management.

There are no known limitations to the application of this method to croplands and grazing lands in the United States although the method provides a limited inference on the fluxes associated with perennial cropland due to no clear impact of managing land with perennial crops compared to natural vegetation.

3.2.6 Methane Emissions From Flooded Rice Cultivation

Box 3-11. Method for Estimating CH_4 Emissions From Rice Cultivation

- This method is based on the IPCC equations (Ogle et al., 2019b) for CH_4 with country-specific factors, which is a Tier 2 method.
- The baseline emission factor—or the typical daily rate at which CH_4 is produced per unit of land area—represents fields that are continuously flooded during the cultivation period, are not flooded during the 180 days before cultivation and receive no organic amendments.
- Differences between the baseline conditions and updated conditions are estimated using scaling factors (e.g., water regime adjustments before and during the cultivation period, organic amendments). Methane scaling factors are from Ogle et al. (2019b).
- The Tier 2 method is introduced with the same IPCC base equation but with regional baseline and scaling factors, including water regime, organic amendments, sulfur amendment, residue litter, and seeding method based on Linquist et al. (2018).
- The method for CH_4 emissions uses entity-specific seasonal parcel data as input into the IPCC equation.

[23] If the information is not available through the USDA-NRCS web soil survey, then the entity should contact USDA-NRCS extension office for guidance on identifying the reference condition.

3.2.6.1 Description of Method

The methodology is formulated on a baseline emission factor, or daily rate, at which CH_4 is produced per unit of land area for rice production with continuously flooded conditions and no organic amendments (see appendix 3A.7 for rationale). The baseline emission factor is scaled according to the specific practices and conditions for the land parcel, including water management, organic amendments, use of sulfur products, residue amount, and seeding practices. Equation 3-25 has been adapted from the IPCC methodology for estimating rice CH_4 emissions from a land parcel (Ogle et al., 2019b).

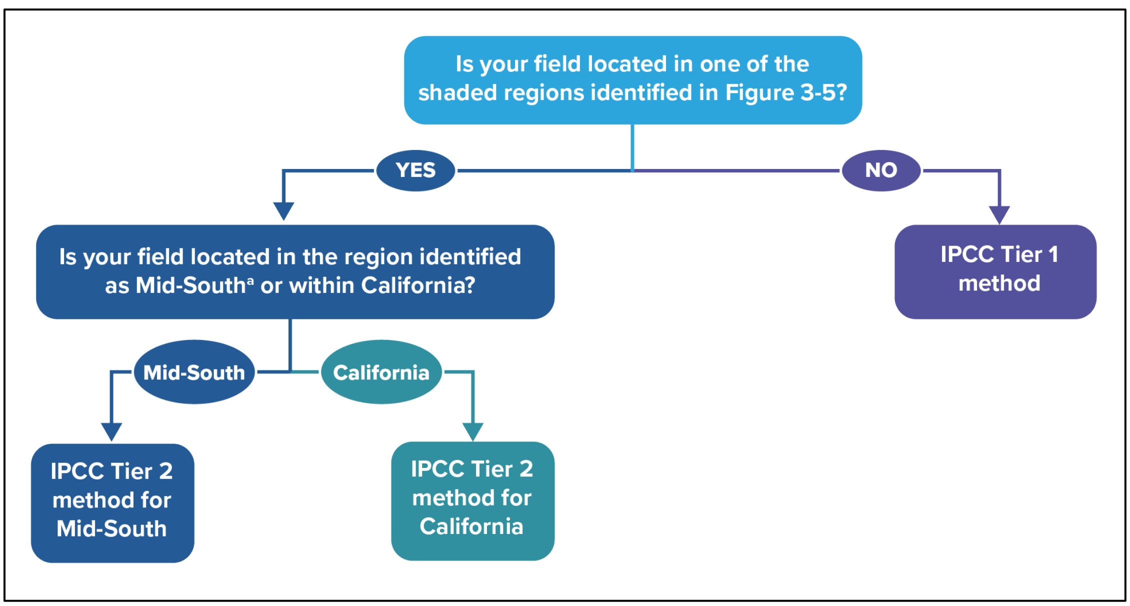
Equation 3-25: Annual Flooded Rice CH_4 Emissions

$$CH_{4Rice} = CH_{4GWP} \times 10^{-3} \times \sum_{GS} EF_i \times t \times A$$

Where:

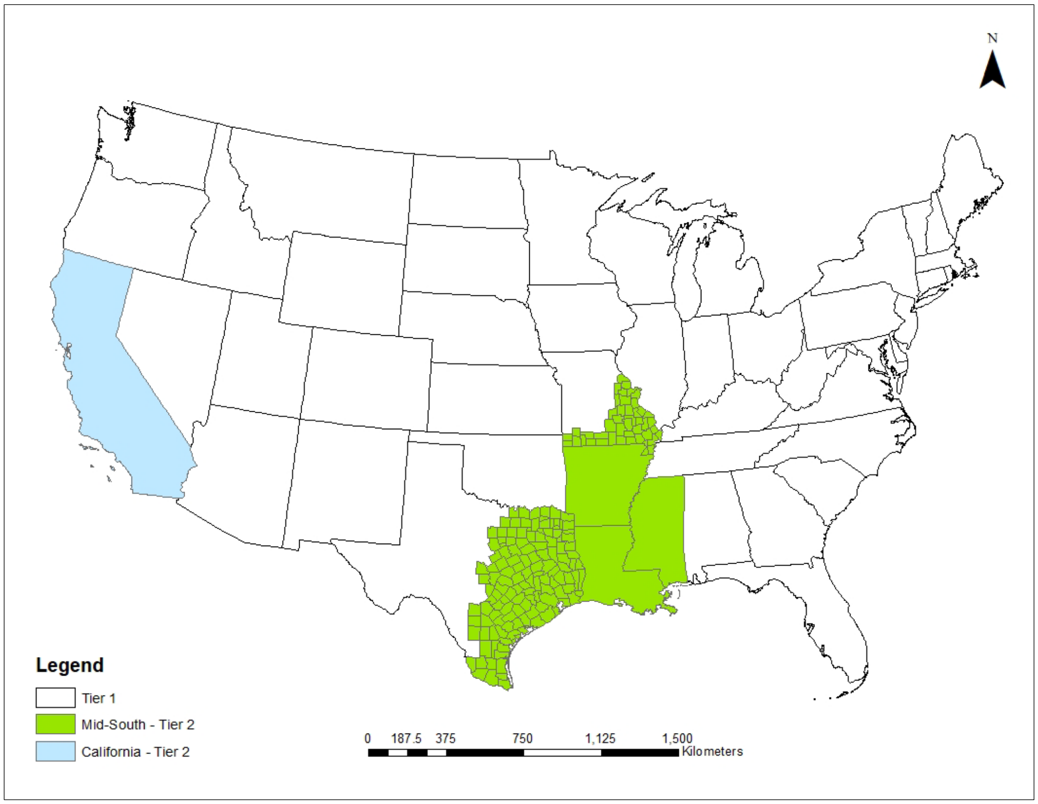
CH_{4Rice}	=	annual CH_4 emissions from rice cultivation (metric tons CO_2-eq)
CH_{4GWP}	=	global warming potential for CH_4 (metric tons CO_2-eq/metric tons CH_4)
EF_i	=	integrated daily emission factor based on management for each growing season (kg CH_4/ha/day)
t	=	cultivation period of rice for each growing season (days)
A	=	harvested area of rice for each growing season (ha)
GS	=	growing seasons for rice cultivation in the reporting year

To determine the daily emission factor to use in equation 3-25, begin with the flowchart in figure 3-4 and the associated location information in figure 3-5.



[a] Verify that the location is within the identified counties in figure 3-5.

Figure 3-4. Decision Tree to Choose Between Tier 1 and Tier 2 Methods to Estimate the Daily Emission Factor for Rice CH_4 Emissions



Shading shows U.S. regions that use the Tier 2 method, including the Mid-South (Arkansas, Louisiana, Mississippi, and certain counties in Missouri and Texas) and California. A full list of the counties is provided in appendix 3A.6.2 that should use the Tier 2 method in Missouri and Texas. Use the Tier 1 method for all other U.S. regions.

Figure 3-5. Use of Tier 2 vs. Tier 1 to Estimate Daily Emission Factor for Rice CH_4 Emissions

Tier 1 Method

The daily emission factor for the Tier 1 method is estimated based on the conditions that influence CH_4 emissions for flooded rice production, including the water management and organic amendment rate (Ogle et al., 2019b). The baseline emission factor represents the emission rate for continuously flooded water management with no organic amendments and no flooding before cultivation.

The rate at which CH_4 is emitted depends on water flooding/drainage regimes and the rates and types of organic amendments applied to the soil. As such, scaling factors for a broad range of management options are provided with this methodology. The factors are differentiated by hydrological context (e.g., irrigated, rainfed, upland), cultivation period flooding regime (e.g., continuous, multiple aerations), time since the last flooding (before cultivation, e.g., over 180 days, under 30 days) and type of organic amendment (e.g., compost, farmyard manure, residue straw). Use equation 3-26 to estimate the daily emission factor for a land parcel with the Tier 1 method (defined by figure 3-5).

Equation 3-26: Flooded Rice CH_4 Emission Factor (Tier 1)

$$EF_i = EF_c \times SF_w \times SF_p \times SF_o$$

Where:

EF_i = integrated daily emission factor based on management for each growing season (kg CH_4/ha/day)

EF_c = baseline emission factor for continuously flooded fields without organic amendments (kg CH_4/ha/day)

SF_w = scaling factor to account for the differences in water regime during the cultivation period (dimensionless)

SF_p = scaling factor to account for the differences in water regime in the preseason before the cultivation period (dimensionless)

SF_o = scaling factor to account for both type and amount of organic amendment applied (dimensionless)

The baseline emission factor for North America associated with the IPCC Tier 1 method (Ogle et al., 2019b) is given in table 3-22.

Table 3-22. Baseline Emission Factor With 95-Percent Confidence Interval

Baseline Emission Factor	EF_c	95-Percent Confidence Interval
North America	0.65	0.44–0.96

Source: Ogle et al., 2019b, Table 5.11, i.e., IPCC Tier 1 factors.

Probability density function has a normal distribution. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

The water regime scaling factors for equation 3-23 are from Ogle et al. (2019b) and are shown below in table 3-23 and table 3-24.

Table 3-23. Rice Water Regime Emission Scaling Factors (During Cultivation Period) With 95-Percent Confidence Intervals

Irrigated or Rainfed and Deep Water	Water Regime During the Cultivation Period	SF_w	95-Percent Confidence Interval
Irrigated	Continuously flooded	1	n/a
	Intermittently flooded—single drainage period	0.71	0.53–0.94
	Intermittently flooded—multiple drainage periods	0.55	0.41–0.72
Rainfed and deep water	Regular rainfed	0.54	0.39–0.74
	Drought prone	0.16	0.11–0.24
	Deep water	0.06	0.03–0.12

Source: Ogle et al., 2019b, Table 5.12, i.e., IPCC Tier 1 factors.

Probability density functions have a normal distribution that can be used to quantify uncertainty, and “n/a” indicates that uncertainty is not applicable because the uncertainty is already incorporated into another factor. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

Table 3-24. Rice Water Regime Emission Scaling Factors (Before Cultivation Period) With 95-Percent Confidence Interval

Water Regime Before the Cultivation Period	SF_p	95-Percent Confidence Interval
Nonflooded preseason < 180 days	1	n/a
Nonflooded preseason > 180 days	0.89	0.80–0.99
Flooded preseason > 30 days	2.41	2.13–2.73
Nonflooded preseason > 365 days	0.59	0.41–0.84

Source: Ogle et al., 2019b, Table 5.13, i.e., IPCC Tier 1 factors.

Probability density functions have a normal distribution that can be used to quantify uncertainty, and "n/a" indicates that uncertainty is not applicable because the uncertainty is already incorporated into another factor. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

To estimate the scaling factor for organic amendments to a land parcel, use equation 3-27.

Equation 3-27: Organic Amendments Scaling Factor

$$SF_o = [1 + \sum(ROA_i \times CFOA_i)]^{0.59}$$

Where:

SF_o = scaling factor for both type and amount of organic amendment

ROA_i = rate of application of organic amendment type i (metric tons/ha)

$CFOA_i$ = conversion factor for organic amendment type i

Organic amendment type i may include straw (incorporated shortly or long before cultivation), compost, farmyard manure, and green manures.

The factors for equation 3-27 are from Ogle et al. (2019b) and are shown below in table 3-25.

Table 3-25. Conversion Factor for Organic Amendment in Rice Cultivation With 95-Percent Confidence Intervals

Organic Amendments	Conversion Factor	95-Percent Confidence Interval
Straw incorporated shortly (< 30 days) before cultivation	1	0.8–1.17
Straw incorporated long (> 30 days) before cultivation	0.19	0.11–0.28
Compost	0.17	0.09–0.29
Farmyard manure	0.21	0.15–0.28
Green manure	0.45	0.36–0.57

Source: Ogle et al., 2019b, Table 5.14, i.e., IPCC Tier 1 factors

Probability density functions have a normal distribution that can be used to quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

Tier 2 Method

A Tier 2 method with region-specific emission factors has been developed for the two primary rice growing regions in the United States, namely the Mid-South (Arkansas, Louisiana, Mississippi, and parts of Missouri and Texas) and California (Linquist et al., 2018). This method is adapted from the

Tier 1 method, with a baseline emission factor for each region given the standard practices and scaling factors to adjust for other practices that may be used by entities. Baseline standard practices for both regions assume no sulfur amendment and no organic amendment. Additional baseline standard practices in the Mid-South include low residue in the field before rice production, irrigation by continuous flooding, no intentional winter flooding, and drill seeding. Standard practices in California include medium to high residue in the field before rice production, irrigation by continuous flooding, intentional winter flooding, and water seeding. Use equation 3-28 to estimate the daily emission factor for a land parcel with the Tier 2 method (defined by figure 3-5).

Equation 3-28: Flooded Rice CH_4 Emission Factor (Tier 2)

$$EF_i = EF_c \times SF_w \times SF_p \times SF_o \times SF_s \times SF_r \times SF_e$$

Where:

EF_i	=	integrated daily emission factor based on management for each growing season (kg CH_4/ha/day)
EF_c	=	baseline emission factor for continuously flooded fields (kg CH_4/ha/day)
SF_w	=	scaling factor for water regime during the cultivation period (dimensionless)
SF_p	=	scaling factor to account for the differences in water regime in the preseason before the cultivation period (dimensionless)
SF_o	=	scaling factor for both type and amount of organic amendment applied (unitless)
SF_s	=	scaling factor for sulfur amendments to soils (dimensionless)
SF_r	=	scaling factor for residue litter amount (dimensionless)
SF_e	=	scaling factor for seeding method in California (dimensionless)

Estimate the baseline emission factor using equation 3-29 and data in table 3-26. The percent of clay is based on the soil texture values in SSURGO for the surface soil layer (Soil Survey Staff, 2023).

Equation 3-29: Flooded Rice Baseline Emission Factor for Tier 2 Method

$$EF_c = \{F_{sa} - [(Clay - BPC) \times C_f]\} \div C_p$$

Where:

EF_c	=	baseline emission factor for continuously flooded fields (kg CH_4/ha/day)
EF_{sa}	=	average seasonal CH_4 emissions (kg CH_4/ha/season)
$Clay$	=	percent of clay associated with the soil texture (percentage); percent clay values that are greater than 54% are assigned a value of 54%
BPC	=	base percent clay (percentage)
C_f	=	clay factor (kg CH_4/ha/season)
C_p	=	cultivation period (days)

Table 3-26. Data for Estimating the Baseline Emission Factor for Mid-South and California Regions With 95-Percent Confidence Intervals in Parentheses

Location	Average Seasonal CH_4 Emission (kg CH_4/ha/Season)	Base Percent Clay (*BPC*, %)	Clay Factor (C_f, kg CH_4/ha/Season)	Cultivation Period (C_p, Days)
Mid-South	194 (129–260)	23 (19–27)	6.1 (1.63–10.55)	133 (125–140)
California	218 (153–284)	46 (39–52)	8.1 (0.80–15.38)	140 (133–148)

Source: Linquist et al., 2018.

Probability density functions have a normal distribution that can be used to quantify uncertainty. The uncertainty in the base percent clay is based on the authors' expert opinion. The confidence intervals represent uncertainty for a regional scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

The scaling factors for the water management regime are provided in table 3-27 from Linquist et al. (2018).

Table 3-27. Region-Specific Rice Water Regime Emission Scaling Factors With 95-Percent Confidence Intervals

Water Management	SF_w	95-Percent Confidence Interval
Continuously flooded	1	n/a
Intermittently flooded—single aeration	0.61	0.53–0.70
Intermittently flooded—multiple aeration	0.17	0.09–0.35

Source: Linquist et al., 2018.

Probability density functions have a normal distribution that can be used to quantify uncertainty, and "n/a" indicates that uncertainty is not applicable because the uncertainty is already incorporated into another factor. The confidence intervals represent uncertainty for a regional scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

Table 3-28 presents the scaling factors for water management during the preseason cultivation period adopted from the Tier 1 method. The baseline in California includes intentional winter flooding and the baseline in the Mid-South includes no intentional winter flooding.

Table 3-28. Rice Water Regime Emission Scaling Factors (Preseason Cultivation Period) With 95-Percent Confidence Intervals

Region	Water Regime Before the Cultivation Period	SFp	95-Percent Confidence Interval
California	Nonflooded preseason	0.41	0.37–0.47
	Flooded preseason > 30 days	1	n/a
Mid-South	Nonflooded preseason	1	n/a
	Flooded preseason > 30 days	2.41	2.13–2.73

Source: Ogle et al., 2019b, Table 5.13, i.e., IPCC Tier 1 factors.

Probability density functions have a normal distribution that can be used to quantify uncertainty, and "n/a" indicates that uncertainty is not applicable because the uncertainty is already incorporated into another factor. The confidence intervals represent uncertainty for a regional scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

To estimate the scaling factors for organic amendment type and rate, use the same equation and factors as the Tier 1 method (equation 3-27 and table 3-25)—but only for compost, farmyard manure, and green manure, as the residue is considered in SF_r.

The scaling factor for sulfur amendments to soils depends on the sulfur application rate. Estimate the factor using equation 3-30, developed by Linquist et al. (2018).

Equation 3-30: Flooded Rice Scaling Factor for Sulfur Amendments to Soils in the Tier 2 Method

With sulfur amendments > 0 and ≤ 338 kg S/ha:

$$SF_s = 1 - (SR \times 0.00133)$$

Where:

SF_s	=	scaling factor for sulfur amendments to soils (dimensionless)
SR	=	sulfur application rate (> 0 and ≤ 338 kg S/ha) (kg S/ha)

Without sulfur amendments or amendments > 338 kg S/ha:

$$SF_s = 1$$

The scaling factors for the previous crop residue are provided in table 3-29 from Linquist et al. (2018). The crop-specific residue classifications are provided in table 3-11.

Table 3-29. Scaling Factors for Region-Specific Residue Amount of Previous Crop With 95-Percent Confidence Intervals

Residue Litter Amount	Region	SF_r	95-Percent Confidence Interval
Low or medium residue (soybean or cotton) or residue removed/burned/grazed	Mid-South	1	n/a
	California	0.46	0.37–0.58
High residue (rice or corn)	Mid-South	2.16	1.72–2.74
	California	1	n/a

Source: Linquist et al., 2018.

Probability density functions have a normal distribution that can be used to quantify uncertainty, and “n/a” indicates that uncertainty is not applicable because the uncertainty is already incorporated into another factor. The confidence intervals represent uncertainty for a regional scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

The scaling factors for the seeding method are provided in table 3-30 from Linquist et al. (2018). These factors are only applied to California; for the Mid-South, use a value of 1.

Table 3-30. Region-Specific Seeding Method Scaling Factors With 95-Percent Confidence Intervals

Region	Seeding Method	SF_e	95-Percent Confidence Interval
California	Water seeded	1	n/a
	Drill seeded with medium to high residue	0.4	0.32–0.52
	Drill seeded with low residue	1	n/a
Mid-South	All seeding types	1	n/a

Source: Linquist et al., 2018.

Probability density functions have a normal distribution that can be used to quantify uncertainty, and "n/a" indicates that uncertainty is not applicable because the uncertainty is already incorporated into another factor. The confidence intervals represent uncertainty for a regional scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

3.2.6.2 Activity Data

The Tier 1 and Tier 2 methods require the following activity data:

- Cultivation period (days)
- Harvested area (ha)
- Water management practices during the cultivation period (e.g., aeration or not)
- Water management during the precultivation period
- Organic amendment type and rate (metric tons/ha)

The Tier 2 method requires additional management activity data:

- Sulfur amendment rate (kg/ha)
- Seeding method

3.2.6.3 Ancillary Data

Ancillary data for the Tier 2 method include soil texture, or more specifically the clay content of the soil. Soil texture data for this method are available from SSURGO (Soil Survey Staff, 2023).

3.2.6.4 Limitations and Uncertainty

Use the explicit model-based method to estimate uncertainty for methane emissions with rice cultivation (see chapter 8). Uncertainty is assumed to be minor for the management activity data provided by the entity, and therefore the values are assumed to be certain. Uncertainties in emission factors are provided in section 3.2.6.1, and are propagated through the calculations using a Monte Carlo simulation. See chapter 8 for more information about the explicit model-based method.

CH_4 emissions are the result of several interacting biological processes, which by nature vary spatially and temporally. The greatest amount of uncertainty is the baseline emission factor, but there is also uncertainty in the scaling factors. Reducing uncertainty in the future will require more data from experimental studies and monitoring networks, and possibly the adoption of other approaches than simple empirical methods, such as process-based simulation models.

The Tier 1 method also has additional uncertainty because the baseline emissions and scaling factors address water and organic matter management and do not include other practices, among them important mitigation options. Further research is required in other regions of the country before region-specific values can be developed to address these limitations. However, it is noteworthy that most of the rice production in the United States occurs in the Mid-South and California regions, which are included in the Tier 2 method.

Although there is uncertainty in the Tier 1 and 2 methods, there are no known limitations in applying the methods to all rice production systems in the United States. However, it is important to apply the correct method to the land parcel following the directions given in figure 3-4.

3.2.7 Carbon Dioxide From Carbonate Lime Applications to Soils

Box 3-12. Method for Estimating CO_2 Emissions From Carbonate Lime Applications

- This method uses the IPCC equation (de Klein et al., 2006) with U.S.-specific emission factors, which is a Tier 2 method.
- The method requires entity-specific annual parcel data as input into the IPCC equation (i.e., the amount of carbonate lime, including crushed limestone and dolomite applied to soils).

3.2.7.1 Description of Method

The approach to estimating CO_2 emissions from liming is a Tier 2 method using equations developed by IPCC (de Klein et al., 2006), with emission factors based on conditions in United States agricultural lands (see appendix 3A.8 for rationale and additional documentation). Use equation 3-31 to estimate annual emissions from carbonate lime additions to a land parcel.

Equation 3-31: Annual Change in Soil Carbon Stocks From Carbonate Lime Application

$$\Delta C_{Lime} = M \times EF \times CO_2MW$$

Where:

ΔC_{Lime}	=	annual change in soil carbon stocks from the lime application (metric tons CO_2-eq)
M	=	annual application of lime as crushed limestone or dolomite (metric tons crushed limestone or dolomite)
EF	=	metric ton CO_2-C emissions per metric ton of lime (metric tons carbon/metric tons lime)
CO_2MW	=	ratio of molecular weight of CO_2 to carbon = 44/12 (metric tons CO_2/metric tons C

The amount of lime applied is provided by the reporting entity. The emission factors for equation 3-28 are provided in table 3-31.

Table 3-31. Emission Factors for Carbonate Lime Applications to Soils With 95-Percent Confidence Intervals in Parentheses (Metric Tons CO_2-C/Tons Carbonate Lime)

Carbonate Lime Type	*EF*	Distribution	Source
Limestone	0.059 (0.001–0.117)	Triangle	West and McBride (2005); U.S. EPA (2020)
Dolomite	0.064 (0.001–0.127)	Triangle	West and McBride (2005); U.S. EPA (2020)

Probability density functions have a triangular distribution that can be used to quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

3.2.7.2 Activity Data

The method requires data on the amount of lime (crushed limestone or dolomite) applied to soils.

3.2.7.3 Limitations and Uncertainty

Use the explicit model-based method to estimate uncertainty for CO_2 emissions from carbonate lime applications to soils (see chapter 8). Uncertainty is assumed to be minor for the management activity data provided by the entity, i.e., the amount of carbonate lime applied to soils, and therefore the values are assumed to be certain. Uncertainty in the emission factor is provided in table 3-31 of section 3.2.7.1 and is propagated through the calculations using a Monte Carlo simulation. See chapter 8 for more information about the explicit model-based method.

Uncertainty in the emission factors is due to variations in emissions related to soil pH and nitrogen fertilizer application rate, which both influence the chemical pathway of lime dissolution (Hamilton et al., 2007; West and McBride, 2005). More specifically, the emission factor will not accurately estimate emissions of lime dissolution if nitric acid (HNO_3) is dominant. Nitric acid is produced when nitrifying bacteria convert ammonium-based (NH_{4+}) fertilizer and other sources of NH_{4+} to nitrate (NO_{3-}). There is also uncertainty because the data that were used in deriving the emission factors, were based on studies conducted in the Midwest. However, the uncertainty in the emission factors addresses this fact with a large range of possible values, which likely covers the true emission rates in all regions of the United States.

Although there are uncertainties in the emission estimates, there are no known limitations that would preclude the application of this method to all croplands and grazing lands in the United States.

3.2.8 Noncarbon Dioxide Emissions From Biomass Burning

Box 3-13. Method for Estimating Non-CO_2 Emissions From Biomass Burning

- The method uses the IPCC Tier 1 equation and emission factors (Aalde et al., 2006).
- Entities provide the specific annual parcel data on area burned for croplands and grazing land, in addition to the crop type(s) and harvest yield data.
- The method requires residue-yield ratios and combustion efficiency as inputs to the IPCC equation, which is provided in this section.

3.2.8.1 Description of Method

The model to estimate non-CO_2 GHG emissions and precursors has been adapted from methods developed by IPCC (Aalde et al., 2006) (see appendix 3A.9 for rationale). Use equation 3-32 to estimate annual emissions due to biomass burning on a parcel of land. As needed, sum the results for the different GHGs (e.g., CH_4, N_2O) to determine the total annual emissions.

Equation 3-32: Annual GHG Emissions From Biomass Burning

$$GHG_{biomassburning} = A \times M \times Ce \times EF \times 10^{-3} \times GHG_{GWP}$$

Where:

$GHG_{biomassburning}$	=	annual emissions of GHG or precursor due to biomass burning (metric tons CO_2-eq)
A	=	area burned (ha)
M	=	mass of fuel available for combustion (metric tons dry matter/ha)
Ce	=	combustion efficiency, dimensionless
EF	=	emission factor (g GHG/kg of burned biomass)
GHG_{GWP}	=	global warming potential for each GHG (metric tons CO_2-eq/metric tons GHG). See chapter 2, table 2-2.

The area of the land parcel is entered by the reporting entity, and the other inputs and emission factors are either calculated or provided in the tables below. Approximate the mass of the fuel combusted in grazing land for a land parcel with equation 3-33.

Equation 3-33: Mass of Fuel for Grazing Land

$$M = (H_{peak} \div C) \times (D \div 100)$$

Where:

M	=	mass of fuel available for combustion (metric tons dry matter/ha)
H_{peak}	=	annual peak aboveground herbaceous biomass carbon stock (metric tons C/ha)
C	=	carbon fraction of aboveground biomass (metric tons C/metric tons dry matter)
D	=	percentage of biomass present at the stage of burning relative to peak (%)

The amount of peak aboveground biomass for grazing land, which is used in equation 3-33, is estimated with equation 3-3 in section 3.2.1. The carbon fraction for grassland herbaceous biomass is 0.47 metric tons of dry matter/metric tons of carbon (Verchot et al., 2006), with a ±5-percent uncertainty for a 95-percent confidence interval (table 3-32). The percentage of biomass present at the stage of burning relative to the peak biomass is determined by the reporting entity or set to a value of 1. The estimated mass of fuel for grazing lands, which is approximated with equation 3-30, does not include the dead biomass. If there is significant residual litter (i.e., dead biomass) in grazing systems, multiply the mass of fuel by 2 as a conservative estimate of the total live and dead biomass on the land parcel, and adjust the carbon fraction to 0.44 metric tons of dry matter/metric ton of carbon (Verchot et al., 2006; mean of grassland herbaceous biomass and litter), with a ±5-percent uncertainty for a 95-percent confidence interval (table 3-32).

Table 3-32. Carbon Fraction for Grassland Herbaceous Biomass With 95-Percent Confidence Intervals in Parentheses (Metric Tons C/Tons Dry Matter)

	Factor	Distribution	Source
C fraction with no significant amount of dead biomass	0.47 (0.45–0.49)	Normal	Verchot et al. (2006), i.e., IPCC Tier 1 factors
C fraction with significant amount of dead biomass	0.44 (0.42–0.46)	Normal	Verchot et al. (2006), i.e., IPCC Tier 1 factors

Verchot et al. (2006) do not provide uncertainty, so uncertainty has been assigned based on the authors' expert opinion. The 95-percent confidence intervals have normal distributions that can be used to propagate error and derivation of confidence intervals through the analysis and quantify in an uncertainty analysis. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

The fuel in cropland is the remaining residue biomass left in the field following harvest. To approximate the mass of the fuel combusted for crop residues, use equation 3-34.

Equation 3-34: Mass of Fuel for Crop Residue

$$M = [(Y \div HI) - Y] \times DM$$

Where:

M	=	mass of fuel available for combustion (metric tons dry matter/ha)
Y	=	crop harvest or forage yield (metric tons yield/ha)
HI	=	harvest index: ratio of yield to aboveground biomass (yield + residue) (metric tons yield/metric tons biomass)
DM	=	dry matter content of harvested crop biomass or forage (metric tons dry matter/metric tons biomass)

The yield data are provided by the reporting entity. The harvest index and dry matter values can be found in table 3-33. If the cropland is burned before harvest, equation 3-34 can be used to approximate the mass of the fuel, which is then divided by the carbon fraction to convert the units into metric tons of dry matter/ha/year.

The mass of fuel for trees in agroforestry, perennial tree crops, and shrub vegetation is based on the methods to estimate aboveground biomass in section 3.2.1.

Combustion efficiency, as defined by IPCC (Aalde et al., 2006), is the proportion of biomass that is burned in a fire. Table 3-33 provides the combustion efficiencies for grazing lands and croplands.

Table 3-33. Combustion Efficiencies (Proportions of Biomass Combusted) With 95-Percent Confidence Intervals in Parentheses

Land Use Category	Combustion Efficiency *(Ce)*	Distribution	Source
Grazing land—early season burn	0.74 (0.37–1)	Normal	Aalde et al. (2006)a, i.e., IPCC Tier 1 factors
Grazing land—mid-late season burn	0.77 (0.26–1)	Normal	Aalde et al. (2006), i.e., IPCC Tier 1 factors
Cropland (residue)—small grains	0.90 (0.45–1)	Normal	Aalde et al. (2006)a, i.e., IPCC Tier 1 factors

Land Use Category	Combustion Efficiency *(Ce)*	Distribution	Source
Cropland (residue)—row crops and other crops	0.80 (0.4–1)	Normal	Aalde et al. (2006)a, i.e., IPCC Tier 1 factors
Shrubs in grazing lands	0.95 (0.48–1)	Normal	Aalde et al. (2006)a, i.e., IPCC Tier 1 factors
Agroforestry/perennial tree crops	0.45 (0.28–0.61)	Normal	Aalde et al. (2006)b, i.e., IPCC Tier 1 factors

Probability density functions have a normal distribution that can be used to quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

[a] Aalde et al. (2006) do not provide uncertainty, so uncertainty has been assigned based on the authors' expert opinion.

[b] Aalde et al. (2006) do not provide values that are specific to agroforestry and perennial trees crops, so the authors chose the values for all "other" temperate forests for this chapter. This value that could be improved in the future through more specific data collection on burning efficiency in agroforestry and perennial tree crop stands.

Emission factors are provided in table 3-34 for GHGs and precursors that form GHGs through various reactions in the atmosphere or biosphere by land use category. Emission factors include physical properties of the fuels.

Table 3-34. Emission Factors for Biomass Burning With 95-Percent Confidence Intervals in Parentheses

Parameter	Emission Factor Value	Distribution	Source
CH_4 factor for grazing land (g CH_4/kg)	2.3 (2.1–2.5)	Normal	Aalde et al. (2006), i.e., IPCC Tier 1 factors
CH_4 factor for cropland residue (g CH_4/kg)	2.7 (1.35–2.84)	Normal	Aalde et al. (2006)[a], i.e., IPCC Tier 1 factors
CH_4 factor for woody biomass (g CH_4/kg)	4.7 (2.82–6.58)	Normal	Aalde et al. (2006)[b], i.e., IPCC Tier 1 factors
N_2O factor for grazing land (g N_2O/kg)	0.21 (0.01–0.40)	Normal	Aalde et al. (2006), i.e., IPCC Tier 1 factors
N_2O factor for cropland residue (g N_2O/kg)	0.07 (0.04–0.11)	Normal	Aalde et al. (2006)[a], i.e., IPCC Tier 1 factors
N_2O factor for woody biomass (g N_2O/kg)	0.26 (0.19–0.33)	Normal	Aalde et al. (2006)[b], i.e., IPCC Tier 1 factors

Probability density functions have a normal distribution that can be used to quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

[a] Aalde et al. (2006) do not provide uncertainty, so uncertainty has been assigned based on authors' expert opinion.

[b] Aalde et al. (2006) do not provide values that are specific to agroforestry and perennial trees crops, so the authors chose the values for extra-tropical forests for this chapter. This value could be improved in the future through more specific data collection on emissions from agroforestry and perennial tree crop stands.

See chapter 6 for methods to estimate non-CO_2 GHG emissions from biomass burning in forest land if there is a land use conversion from forest land to cropland or grazing land.

3.2.8.2 Activity Data

The following activity and related data are needed to apply the method:

- Area burned for croplands and grazing land.
- Crop type and harvest yield data for crops grown in fields with residue burning management.
- Amount of aboveground biomass before the fire in grazing lands based on the peak biomass production and percentage of the biomass in the parcel relative to the peak biomass at the time of the fire.
- Amount of aboveground woody biomass before the fire in agroforestry and perennial tree crops, as well as aboveground shrub biomass in the land parcel.

In some years, the entity may not harvest the crop due to drought, pest outbreaks, or other reasons for crop failure. If residues are burned, the entity should provide the average yield that has been harvested for the specific crop over the past 5 years, along with an approximate percentage of average crop growth that occurred prior to burning. The mass of the fuel is estimated using equation 3-31, then multiplied by the proportion of crop growth that occurred prior to burning.

3.2.8.3 Limitations and Uncertainty

Use the explicit model-based method to estimate uncertainty for non-CO_2 emissions from biomass burning (see chapter 8). Uncertainty is assumed to be minor for the management activity provided by the entity and related data, including crop yields, peak forage, and relative amount of crop or forage growth compared to the peak production, and therefore the values are assumed to be certain. Uncertainties in the emission factor and other parameters are provided in section 3.2.8.1, including mass of fuel for woody biomass, carbon fractions, dry matter contents, harvest indices, combustion efficiencies, and emission factors, and are propagated through the calculations using a Monte Carlo simulation. See chapter 8 for more information about the explicit model-based method.

Although there is uncertainty in the emission estimates, there are no major limitations on the application of this method to all croplands and grazing lands in the United States.

3.2.9 Carbon Dioxide From Urea Fertilizer Applications

Box 3-14. Method for Estimating CO_2 Emissions From Urea Fertilizer Application

- This method uses the IPCC Tier 1 equation and emission factors developed by de Klein et al. (2006).
- The entity provides specific annual parcel data on urea fertilizer addition as input into the IPCC equation.

3.2.9.1 Description of Method

The equation to estimate CO_2 emissions from urea application has been adopted from the methodology developed by IPCC and uses the IPCC default emission factor (de Klein et al., 2006) (see appendix 3A.10 for rationale). Use equation 3-35 to estimate the annual CO_2 emission from a land parcel where urea-based fertilizers have been applied.

Equation 3-35: Annual CO_2 Emissions From Urea Fertilization

$$C_{urea} = M \times EF \times CO_2MW$$

Where:

C_{urea} = annual release of carbon from urea added to the soil (metric tons CO_2-eq)

M = annual amount of urea fertilization (metric tons of urea)

EF = emission factor, based on the proportion of carbon in urea (metric tons CO_2-C/metric tons urea)

CO_2MW = ratio of molecular weight of CO_2 to carbon = 44/12 (metric tons CO_2/metric tons C)

The amount of urea fertilization is provided by the reporting entity, and the emission factor for urea fertilization is in the table below.

Table 3-35. CO_2 Emission Factor From Urea Fertilization With 95-Percent Confidence Interval in Parentheses

	Emission Factor	Distribution	Data Source
Urea fertilization (metric tons CO_2-C/metric ton urea)	0.20 (0.10–0.20)	Triangle	de Klein et al. (2006), i.e., IPCC Tier 1 factors

Probability density functions have a triangular distribution that can be used to quantify uncertainty. The confidence intervals represent uncertainty for a national scale application of the method, and so there may be additional uncertainty with application of this method at the entity scale that is not quantified.

3.2.9.2 Activity Data

This method requires data on the amount of urea fertilizer applied to soils. Any fertilizer containing urea should be included, such as urea ammonium nitrate, but the mass is based on the portion that is urea.

3.2.9.3 Limitations and Uncertainty

Use the explicit model-based method to estimate uncertainty for CO_2 emissions from urea application to soils (see chapter 8). Uncertainty is assumed to be minor for the management activity data provided by the entity, i.e., the amount of urea applied to soils, and therefore the values are assumed to be certain. Uncertainty in the emission factor is provided in table 3-35 of chapter 3 and is propagated through the calculations using a Monte Carlo simulation. See chapter 8 for more information about the explicit model-based method.

Although there is uncertainty, there are no major limitations on the application of this method to all croplands and grazing lands in the United States.

3.3 Chapter 3 References

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Appendix 3-A: Method Documentation

3-A.1 Biomass Carbon Stock Changes

3-A.1.1 Rationale for Method

Both IPCC (Ogle et al., 2019b) and the U.S. EPA (2020) consider herbaceous biomass carbon stocks to be ephemeral and recognize that there are no net emissions to the atmosphere following crop growth and senescence during one annual crop cycle (West et al., 2011). However, with respect to changes in land use (e.g., forest to cropland), IPCC (Ogle et al., 2019b) recommends that cropland biomass be counted in the year that land conversion occurs, and the same assumption also applies for grassland (McConkey et al., 2019). According to IPCC, estimating the herbaceous biomass carbon stock during changes in land use is necessary to quantify the influence of herbaceous plants on CO_2 uptake from the atmosphere and storage in the terrestrial biosphere. However, this method does not recognize changes in herbaceous biomass that occur with changes in crop rotations, nor does it recognize long-term increases in annual crop yields. The method in this chapter is considered a Tier 2 method as defined by IPCC because it incorporates factors that are based on U.S.-specific data and differs from the methodology in U.S. EPA (2020) because of this.

Agroforestry (along with other woody vegetation in croplands, such as orchards and vineyards) can sequester significant amounts of new carbon within long-lived biomass over time with woody plant growth. A measurement-based method has been selected for entity-scale reporting of biomass carbon stock changes in croplands and grazing lands due to limited data availability on agroforestry stands and other woody crops and shrubs. Well-established methods for estimating the woody biomass in forest landscapes are described in chapter 5. These methods form the basis for estimating woody biomass in croplands and grazing lands but were modified to fit an agricultural context. A combination of Tier 1 and 3 methods using entity-specific data is recommended for estimating the carbon stock changes associated with agroforestry and woody crops.

3-A.1.2 Technical Documentation

The aboveground biomass estimation for trees relies on a dbh-based allometric equation derived from a meta-analysis of 2,928 biomass equations for trees in the United States (Chojnacky et al., 2014). Equation parameters are available for 13 conifer, 18 hardwood, and 4 woodland taxa, representing 129 tree species (table 3A-1). Table 3A-1, table 3A-2, and table 3A-3 provide the species associated with the 35 taxon groups. This forest-based approach will likely produce conservative (underestimated) values of carbon stocks and stock changes in cropland and grazing lands since trees in windbreaks and other more open plantings have been documented to have greater live biomass than predicted by forest-based allometric equations (Zhou et al., 2015). Belowground biomass is estimated based on a ratio of root component biomass to total aboveground biomass (Chojnacky et al., 2014). Increased partitioning of biomass carbon to roots is observed in open-grown trees (Ritson and Sochacki, 2003), so forest-based approaches will give conservative (underestimated) values for this component. This approach is a considered a Tier 3 method as defined by IPCC because it involves measurement of aboveground biomass.

Since allometric equations for nontree woody species, i.e., shrubs and vineyards, are not available, regional Tier 1 defaults are used to estimate woody biomass for these species' groups (Ogle et al., 2019b). For shrubs, the temperate hedgerow default for North America was used to establish a carbon accumulation rate of 0.00128 metric tons/shrub/year for up to 30 years, after which additional carbon is not expected. For vines (e.g., grapes), use the temperate domain default for an aboveground biomass accumulation rate of 0.28 tons C/ha/year over a 20-year period. This method is a considered a Tier 1 method as defined by IPCC. Belowground biomass for vineyards is not estimated.

Although litter and woody debris are important components in forests, they are generally minor components in agroforestry and thus are not considered in this method (Schoeneberger et al., 2017).

Table 3A-1. Thirteen Taxon Groupings for 45 Conifer Species (or Species Groups)

Taxon	Genus and Species	Common Name
Abies < 0.35 spg[a]	*Abies balsamea*	Fir, balsam
	A. fraseri	Fir, Fraser
	A. lasiocarpa	Fir, subalpine
Abies ≥ 0.35 spg	*A. amabilis*	Fir, Pacific silver
	A. concolor	Fir, white
	A. grandis	Fir, grand
	A. magnifica	Fir, California red
	A. procera	Fir, noble
	Abies spp.	Fir, Pacific silver/noble/other
Cupressaceae < 0.30 spg	*Thuja occidentalis*	Cedar, northern white
Cupressaceae 0.30–0.39 spg	*Calocedrus decurrens*	Incense cedar
	Sequoiadendron giganteum	Sequoia, giant
	T. plicata	Cedar, western red
Cupressaceae ≥ 0.40 spg	*Chamaecyparis nootkatensis*	Cedar, Alaska
	Juniperus virginiana	Juniper, eastern redcedar
Larix	*Larix laricina*	Tamarack
	L. occidentalis	Tamarack, western larch
	Larix spp.	Tamarack, larch (introduced)
Picea < 0.35 spg	*Picea engelmannii*	Spruce, Engelmann
	P. sitchensis	Spruce, Sitka
Picea ≥ 0.35 spg	*P. abies*	Spruce, Norway
	P. glauca	Spruce, white
	P. mariana	Spruce, black
	P. rubens	Spruce, red
Pinus < 0.45 spg	*Pinus albicaulis*	Pine, whitebark
	P. arizonica	Pine, Arizona
	P. banksiana	Pine, jack
	P. contorta	Pine, lodgepole
	P. jeffreyi	Pine, Jeffrey
	P. lambertiana	Pine, sugar
	P. leiophylla	Pine, Chihuahua
	P. monticola	Pine, western white
	P. ponderosa	Pine, ponderosa

Taxon	Genus and Species	Common Name
	P. resinosa	Pine, red
	Pinus spp.	Pine, ponderosa/lodgepole/sugar
	P. strobus	Pine, eastern white
Pinus ≥ 0.45 spg	*P. echinata*	Pine, shortleaf
	P. elliottii	Pine, slash
	P. palustris	Pine, longleaf
	P. rigida	Pine, pitch
	P. taeda	Pine, loblolly
Pseudotsuga	*Pseudotsuga menziesii*	Douglas fir
Tsuga < 0.40 spg	*Tsuga canadensis*	Hemlock, eastern
Tsuga ≥ 0.40 spg	*T. heterophylla*	Hemlock, western
	T. mertensiana	Hemlock, mountain

Source: Chojnacky et al., 2014.

[a] spg = specific gravity of wood on a green volume to dry-weight basis.

Table 3A-2. Eighteen Taxon Groupings for 70 Hardwood Species (or Species Groups)

Taxon	Family	Genus and Species	Common Name
Aceraceae < 0.50 spg[a]	Aceraceae	*Acer macrophyllum*	Maple, bigleaf
	Aceraceae	*A. pensylvanicum*	Maple, striped
	Aceraceae	*A. rubrum*	Maple, red
	Aceraceae	*A. saccharinum*	Maple, silver
	Aceraceae	*A. spicatum*	Maple, mountain
Aceraceae ≥ 0.50 spg	Aceraceae	*A. saccharum*	Maple, sugar
Betulaceae < 0.40 spg	Betulaceae	*Alnus rubra*	Alder, red
	Betulaceae	*Alnus spp.*	Alder, Sitka
Betulaceae 0.40–0.49 spg	Betulaceae	*Betula papyrifera*	Birch, paper
	Betulaceae	*B. populifolia*	Birch, gray
Betulaceae 0.50–0.59 spg	Betulaceae	*B. alleghaniensis*	Birch, yellow
Betulaceae ≥ 0.60 spg	Betulaceae	*B. lenta*	Birch, sweet
	Betulaceae	*Ostrya virginiana*	Hophornbeam
Cornaceae/Ericaceae/ Lauraceae/Platanaceae/ Rosaceae/Ulmaceae	Cornaceae	*Cornus florida*	Dogwood
	Cornaceae	*Nyssa aquatica*	Tupelo, water
	Cornaceae	*N. sylvatica*	Tupelo, blackgum
	Ericaceae	*Arbutus menziesii*	Madrone, Pacific
	Ericaceae	*Oxydendrum arboreum*	Sourwood
	Ericaceae	*Umbellularia californica*	California bay laurel
	Lauraceae	*Sassafras albidum*	Sassafras
	Platanaceae	*Platanus occidentalis*	Sycamore
	Rosaceae	*Amelanchier spp.*	Serviceberry
	Rosaceae	*Prunus pensylvanica*	Cherry, pin
	Rosaceae	*P. serotina*	Cherry, black

Taxon	Family	Genus and Species	Common Name
	Rosaceae	*P. virginiana*	Cherry, chokecherry
	Rosaceae	*Sorbus americana*	Sorbus, mountain ash
	Ulmaceae	*Ulmus americana*	Elm
	Ulmaceae	*Ulmus spp.*	Elm
Fabaceae/Juglandaceae, Carya	Juglandaceae	*Carya illinoinensis*	Pecan
	Juglandaceae	*C. ovata*	Hickory, shagbark
	Juglandaceae	*Carya spp.*	Hickory
Fabaceae/Juglandaceae, other	Fabaceae	*Robinia pseudoacacia*	Locust, black
Fagaceae, deciduous	Fagaceae	*Castanea dentata*	Chestnut, American
	Fagaceae	*Fagus grandifolia*	Beech
	Fagaceae	*Quercus alba*	Oak, white
	Fagaceae	*Q. coccinea*	Oak, scarlet
	Fagaceae	*Q. ellipsoidalis*	Oak, pin
	Fagaceae	*Q. falcata*	Oak, red southern
	Fagaceae	*Q. macrocarpa*	Oak, bur
	Fagaceae	*Q. nigra*	Oak, water
	Fagaceae	*Q. prinus*	Oak, chestnut
	Fagaceae	*Q. rubra*	Oak, red northern
	Fagaceae	*Quercus spp.*	Oaks
	Fagaceae	*Q. stellata*	Oak, post
	Fagaceae	*Q. velutina*	Oak, black
Fagaceae, evergreen	Fagaceae	*Chrysolepis chrysophylla*	Chinkapin, golden
	Fagaceae	*Lithocarpus densiflorus*	Tanoak
	Fagaceae	*Q. douglasii*	Oak, blue
	Fagaceae	*Q. laurifolia*	Oak, laurel
	Fagaceae	*Q. minima*	Oak, dwarf live
Hamamelidaceae	Hamamelidaceae	*Liquidambar styraciflua*	Sweetgum
Hippocastanaceae/Tiliaceae	Hippocastanaceae	*Aesculus flava*	Aesculus, yellow buckeye
	Tiliaceae	*Tilia americana*	Basswood
	Tiliaceae	*T. americana. var. heterophylla*	Basswood, white
Magnoliaceae	Magnoliaceae	*Liriodendron tulipifera*	Tulip poplar
	Magnoliaceae	*Magnolia fraseri*	Magnolia, Fraser
	Magnoliaceae	*M. virginiana*	Magnolia, sweetbay
Oleaceae < 0.55 spg	Oleaceae	*Fraxinus nigra*	Ash, black
	Oleaceae	*F. pennsylvanica*	Ash, green
	Oleaceae	*Fraxinus spp.*	Ash
Oleaceae ≥ 0.55 spg	Oleaceae	*F. americana*	Ash, white

Taxon	Family	Genus and Species	Common Name
Salicaceae < 0.35 spg	Salicaceae	*Populus balsamifera*	Populus, balasm poplar
	Salicaceae	*P. balsamifera. ssp. trichocarpa*	Populus, black Cottonwood
	Salicaceae	*Populus spp.*	Populus, cottonwood
Salicaceae ≥ 0.35 spg	Salicaceae	*P. deltoides*	Populus, cottonwood eastern
	Salicaceae	*P. grandidentata*	Populus, aspen bigtooth
	Salicaceae	*Populus spp.*	Populus, cottonwood
	Salicaceae	*P. tremuloides*	Populus, aspen quaking
	Salicaceae	*Salix alba*	Willow, white
	Salicaceae	*Salix spp.*	Willow

Source: Chojnacky et al., 2014.

[a] spg = specific gravity of wood on a green volume to dry-weight basis.

Table 3A-3. Four Taxon Groupings for 15 Woodland Species (or Species Groups)

Taxon	Family	Genus and Species	Common Name
Cupressaceae	Cupressaceae	*Cupressus spp.*	Cypress, pygmy
	Cupressaceae	*Juniperus monosperma*	Juniper, oneseed
	Cupressaceae	*J. occidentalis*	Juniper, western
	Cupressaceae	*J. osteosperma*	Juniper, Utah
Fabaceae/Rosaceae	Fabaceae	*Cercidium microphyllum*	Paloverde, yellow
	Fabaceae	*Prosopis spp.*	Mesquite
	Rosaceae	*Cercocarpus ledifolius*	Mountain mahogany
	Rosaceae	*C. montanus. var. pauciden*	Mountain mahogany
Fagaceae	Fagaceae	*Quercus douglasii*	Oak, blue
	Fagaceae	*Q. gambelii*	Oak, Gambel
	Fagaceae	*Q. hypoleucoides*	Oak, silverleaf
	Fagaceae	*Quercus (live) spp.*	Oak, evergreen spp.
Pinaceae	Pinaceae	*Pinus cembroides*	Pine, pinyon
	Pinaceae	*P. edulis*	Pine, pinyon
	Pinaceae	*P. monophylla*	Pine, pinyon singleleaf

Source: Chojnacky et al., 2014.

3-A.2 Soil Carbon Stock Changes

3-A.2.1 Rationale for Method

The Tier 3 method using the DayCent model is selected for estimating SOC stock changes on mineral soils because it has been well-tested and demonstrated to represent SOC dynamics in U.S. croplands and grazing lands for application in an operational tool to estimate SOC stock changes in mineral soils (Parton et al., 1987, 1993). In addition, uncertainties have been fully quantified using an empirical method with data that have not been used to parameterize the model (U.S. EPA, 2020; Ogle et al., 2007). Moreover, Del Grosso et al. (2011) demonstrated a significant reduction in uncertainty associated with the more advanced approach using the DayCent model compared to the lower tier methods for U.S. agricultural lands. While uncertainties are reduced with these methods compared to lower tier methods, this does not imply that these methods are perfect estimators. There are larger uncertainties, particularly at the parcel scale, and as discussed in appendix 3B, there are still knowledge and data gaps that need to be filled to improve the methods, and reduce uncertainties.

The DayCent model captures key processes, land use, and management practices that are driving SOC stock changes in U.S. agricultural lands. The model represents the influence of soil moisture dynamics, plant production, and thermal controls on net primary production and decomposition with a time step of a month or less. The model captures most land use and management impacts on cropland and grazing land systems, as well as conversion from other land uses into these systems (Paustian et al., 2016). SOC pools can be modified due to changes in carbon inputs and outputs (Paustian et al., 1997), and the change in inputs over time due to interannual variability and longer term trends in net primary production, as well as differences in carbon removals from harvesting and residue management practices. External carbon inputs will also have an influence on the SOC stocks, such as manure, compost, sewage sludge, wood chips, and biochar amendments. DayCent can represent the influence of these practices, with the exception of biochar. Consequently, another model has been selected for representing the influence of biochar amendments on mineral SOC stock changes. Carbon outputs will change due to interannual variability and longer term trends in microbial decomposition rates, and is influenced by practices such as tillage management, which are also addressed in the DayCent model framework. The DayCent model has also been improved for modeling SOC stock changes using a Bayesian calibration method (Gurung et al., 2020).

The Tier 3 method is not applied to all U.S. agricultural lands because the model lacks the structure or has not been adequately tested for certain soils types and crops, which includes several crops; mineral soils that are very gravelly, cobbly, or shaley (more than 35 percent coarse fragments by volume); and organic soils (i.e., *Histosols*) (see figure 3-2 for more information). In these cases, a Tier 2 method is applied to estimate the SOC stock changes using country-specific stock change factors for most management practices on mineral soils and country-specific emission factors for organic soils. This method has been developed specifically for conditions in the United States and is used in the U.S. GHG Inventory (U.S. EPA, 2020; Ogle et al., 2003, 2006).

The biochar model is based on accounting for inputs and outputs. The model is grounded in empirical data using recent meta-analyses to ensure that it is representative of current data. No well-calibrated process model exists at this time, and so a method developed by IPCC was chosen for this chapter (Ogle et al., 2019a). The IPCC approach (Ogle et al., 2019a) has been adapted for reporting in the United States using material properties (namely the molar ratio of hydrogen to organic carbon, $H{:}C_{org}$) rather than the pyrolysis temperature (Woolf et al., 2021). Material properties provide better predictions and monitoring of biochar quality. The values for carbon fraction of biochar (F_C) have also been updated from the IPCC biochar method to incorporate additional publications (Woolf et al., 2021). The equation to predict biochar persistence is based on both laboratory and field experiments and is consistent with long-term (centennial and millennial) dynamics of natural biochar materials (Bird et al., 2015; Ogle et al., 2019a; Lehmann et al., 2021; Bowring et al, 2022). Short-term data will tend to underestimate rather than overestimate persistence (Lehmann et al., 2015; Wang et al., 2016), making an empirical model that includes data from incubations and field trials conservative. Furthermore, meta-analyses have consistently shown that the addition of biochar on average decreases rather than increases the mineralization of native SOC, on the order of a 4-percent decrease (e.g., Wang et al., 2016; Ding et al., 2018), in the long term. Thus, exclusion of the impact of biochar on native SOC is conservative for estimating the influence of biochar on SOC stock changes.

3-A.2.2 Technical Documentation

SOC stocks change at relatively slow rates from current land use and management activity and integrate effects over time from a variety of land use and management practices as well as other environmental drivers. There can also be a strong influence of past land use and management, and some practices such as biochar amendments can lead to long-term carbon storage in soils over centuries. This section provides more information about the models that are used to capture the influence of entity-scale management on SOC stock changes.

Tier 3 method for mineral soils: The DayCent model simulates plant production by representing long-term effects of land use and management on net primary production (NPP), as influenced by selection of crops and forage grasses. The influence of management practices on NPP is also simulated, including mineral fertilization, organic amendments, irrigation, fertigation, liming, green manures, cover crops, cropping intensity, hay or pasture in rotation with annual crops, grazing intensity based on stocking rate, and bare fallow. Nutrient and moisture dynamics are influenced by soil characteristics, such as soil texture. The method addresses interannual variability due to annual changes in management and the effect of weather on NPP.

In the DayCent model, three SOC pools are included representing active, slow, and passive soil organic matter, which have different turnover times. It is generally considered that the active carbon pool is microbial biomass and associated metabolites having a rapid turnover (months to years), the slow carbon pool has intermediate stability and turnover times (decades), and the passive carbon pool represents highly processed and humified decomposition products with longer turnover times (centuries). However, these pools are kinetically defined and do not necessarily represent explicit fractions of SOC that can be isolated in a laboratory. Soil texture, temperature, moisture availability, aeration, burning, and other factors are represented in the simulations that influence the decomposition and loss of carbon from these pools. The model also captures interannual variability in decomposition of SOC related to weather patterns.

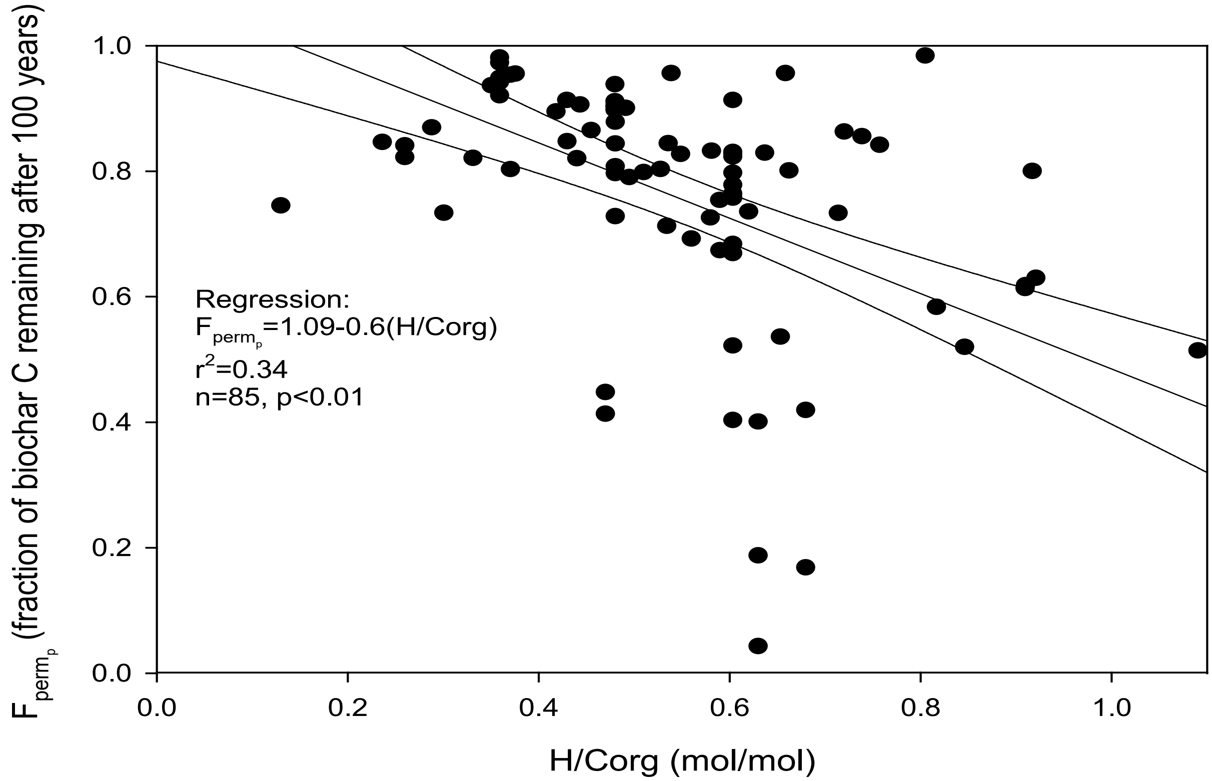
The model simulates management practices influencing SOC pools. These practices include addition of carbon in manure and other organic amendments, such as compost, wood chips, and biochar; tillage intensity; residue management (retention of residues in field without incorporation, retention in the field with incorporation, and removal with harvest, burning, or grazing). The influence of bare and vegetated fallows is represented, in addition to irrigation effects on decomposition in cropland and grazing land systems. The model can also simulate setting aside cropland from production, as well as various grazing management regimes related to specific timing of grazing and intensity.

A water/soil moisture submodel (e.g., Parton et al., 1987) is used to represent the influence of weather, irrigation, crop type, and management on soil moisture dynamics. This impact is particularly important because moisture tends to be a more proximal factor controlling SOC dynamics, which, in turn, is influenced by land use and management activity. For example, irrigation influences SOC stocks because irrigation influences the moisture regime, which in turn influences plant production and carbon inputs to the soil. See Ogle et al. (2010) and U.S. EPA (2020) for more documentation on this method.

Tier 2 method for mineral soils: The Tier 2 method is not a dynamic model, as represented by DayCent, but rather an empirical method that represents linear changes in SOC stocks over 20-year periods. Statistical models have been developed to represent the influence of land use, management, and carbon input on SOC stock changes (Ogle et al., 2003, 2006). Each of these three variables is represented by discrete categories, such as high, medium, and low carbon input, and a carbon stock change factor is estimated for changes among categories using the statistical model. Variability in climate and soils is addressed with different factors for reference carbon stocks and the stock change factors, but these factors are fixed across time so they do not represent interannual variability, particularly as related to weather. However, this method is considered more general, and can be applied in circumstances in which the DayCent model has not been tested. See Ogle et al. (2003, 2006) and U.S. EPA (2020) for more documentation on this method.

Biochar amendments to mineral soils: The carbon content of biochar depends on feedstock properties (namely the carbon properties and the ash content) as well as the conditions of conversion (namely the pyrolysis temperature, time, and pressure). The carbon concentration of biochar *(F_C)* was calculated from regressions by Neves et al. (2011) and corrected for ash content using biochar yield from Woolf et al. (2014). Data on ash, lignin, and carbon content of biomass feedstocks, which are parameters in these regression equations, were taken from ECN (2021). Biochar persistence was calculated using the relationship between biochar properties and mineralization applying the same criteria as in Ogle et al. (2019a). The $H{:}C_{org}$ ratio is strongly correlated with the degree of fused aromatic ring structures (Bird et al., 2015; Knicker, 2007; Singh et al., 2012), and therefore with the ability of microorganisms to mineralize organic matter (Knicker, 2007; Lehmann et al., 2015). Mineralization experiments were taken from studies that used at least 1 year of replicated data with sufficient measurements over the experimental period to develop a double-exponential model. The rate constants were converted to 10.9 °C (Woolf et al., 2021), which is the mean annual air temperature of cropland in the United States. The mean air temperature was estimated based on the spatial mean of WorldClim 2.1 data (Fick and Hijmans, 2017) over the distribution of cropland in the United States according to Ramankutty et al. (2008). The rate constants were based on using temperature responses with Q_{10} as a function of incubation temperature according to the equation $Q_{10} = 1.1 + 12e^{-0.19T}$ (Lehmann et al., 2015). The F_{perm} factor is derived from the relationship between $H{:}C_{org}$ ratios of biochars and mineralization (figure 3A-1), using the sources cited beneath the figure.

Organic soils: Drainage of organic soils for crop production leads to net annual emissions due to increased decomposition of the organic matter after lowering the water table and creating aerobic conditions in the upper layers of the soil (Allen, 2012; Armentano and Menges, 1986). There has been less evaluation of process-based models for organic soils, particularly the simulation of water table dynamics throughout the year, which influences the emission rate. The method incorporates U.S. emission rates associated with region-specific drainage patterns (Ogle et al., 2003), so it is a Tier 2 method as defined by IPCC (Ogle et al., 2019a). See Ogle et al. (2003) and U.S. EPA (2020) for more documentation on this method.



Mineralization rates adjusted to 10.9 °C.

Cumulative mineralization data (only studies with at least 1 year of data were included) were fit with a double exponential model (a triple exponential model for Herath et al., 2015, as shown in the original article).

Sources: Major et al., 2010; Zimmerman, 2010; Singh et al., 2012, 2015; Zimmerman and Gao, 2013; Fang et al., 2014, 2019; Herath et al., 2015; Dharmakeerthi et al., 2015; Budai et al., 2016; Wu et al., 2016; Liu et al., 2020.

Figure 3A-1. Relationship Between the *H:Corg* Ratios of Biochars and Mineralization

3-A.3 Soil Nitrous Oxide

3-A.3.1 Rationale for Method

N_2O fluxes are difficult to measure due to the labor required to sample emissions, combined with high spatial and temporal variability. Agronomic practices that affect N_2O fluxes in a soil, climate, or site-year may have little or no measurable effect in others. Consequently, considerable care is required to ensure that methods to estimate changes in emissions for a particular cropping practice are accurate and robust for the geographic region for which they are proposed or are sufficiently generalizable to be accurate in aggregate. There are two methods that are most commonly applied for estimating soil N_2O emissions, including empirical approaches that rely on statistical modeling or derivation of emission factors, and process-based models that rely on mechanistic frameworks for simulating production, water flows, temperature regimes and soil organic matter dynamics in order to predict N_2O emissions from nitrification and denitrification (Chen et al., 2008; Del Grosso et al., 2010). A key advantage of simulation models is that they are generalizable to a wide variety of soils, climates, and cropping systems, allowing factors to interact in complex ways that may be difficult to predict with less sophisticated approaches.

Model testing was conducted to evaluate the performance of a Tier 3 method using the DayCent process-based model (Parton et al., 1998; Del Grosso et al., 2005), relative to the IPCC Tier 1 method and 2014 USDA entity-scale reporting method (Ogle et al., 2014). Selected sites were compared based on the following criteria: a) data must be produced from a field experiment, b) required sufficient frequency and intensity of measurements to estimate annual N_2O emissions, and c) the experiment had not been used to calibrate the DayCent model to ensure an independent evaluation of the methods. The dataset included 7 sites with 62 observations of soil N_2O emissions (table 3A-4). This is a relatively small dataset, highlights the need for more experiments and monitoring of N_2O emissions to independently evaluate models and methods.

Table 3A-4. Sites With N_2O Observations Used for Model Evaluation and Comparisons

Site and Reference	Treatments	Years	Crop(s)	N Rate kg N/ha
Fort Collins, CO Halvorson et al. 2016	N fertilization rate and fertilizer type (manure, urea, SuperU)	2012–2013	Corn	0–480
Bozeman, MT Dusenbury et al. 2008	Tillage, crop rotation and N fertilization rate	2004–2005	Winter wheat/spring pea	0–150
Elora, Ontario Meyer-Aurich et al. 2004	Tillage by N fertilization rate	2000–2004	Corn/soybean/winter wheat	0–150
Glenlea, Manitoba Maas et al. 2013	Tillage and crop rotation	2006–2011	Corn, alfalfa, spring wheat, rapeseed, barley	0–146
Ottawa, Ontario Sansoulet et al. 2014	Recommended N fertilization rate	2007	Spring wheat	60–78
Edinburgh, Scotland Clayton et al. 1997	Unfertilized grassland	1992	Ryegrass	0
Fendt, Bavaria Lu et al. 2016	Extensive and intensive grassland systems	2012–2013	Grass legume	61–365

The model estimates are compared to the observed soil N_2O emissions from the experimental sites using several metrics, including the root mean square error (RMSE), mean difference between observations and model estimates, and fitting a linear regression model to estimate the relationship between the observations and model estimates. The RMSE provides an inference on the level of precision in the modeled estimates and the mean difference provide an inference on average bias in the model estimates. The regression fit provides inference on the accuracy of the relationship between modeled and observed emissions. The fitted regression line closer to the 1:1 reference line in addition to a lower r^2 value represents a more accurate model for estimating soil N_2O emissions.

The Tier 3 DayCent model and IPCC Tier 1 method have closer agreement with annual N_2O emissions derived from observational datasets than the 2014 USDA entity-scale reporting method (figure 3A-2, table 3A-5). The DayCent model has the lowest RMSE, followed by the IPCC method and the 2014 USDA entity-scale reporting method. The IPCC method has the lowest bias on average according to the mean difference statistic, followed by the 2014 USDA entity-scale reporting method, and the DayCent model.

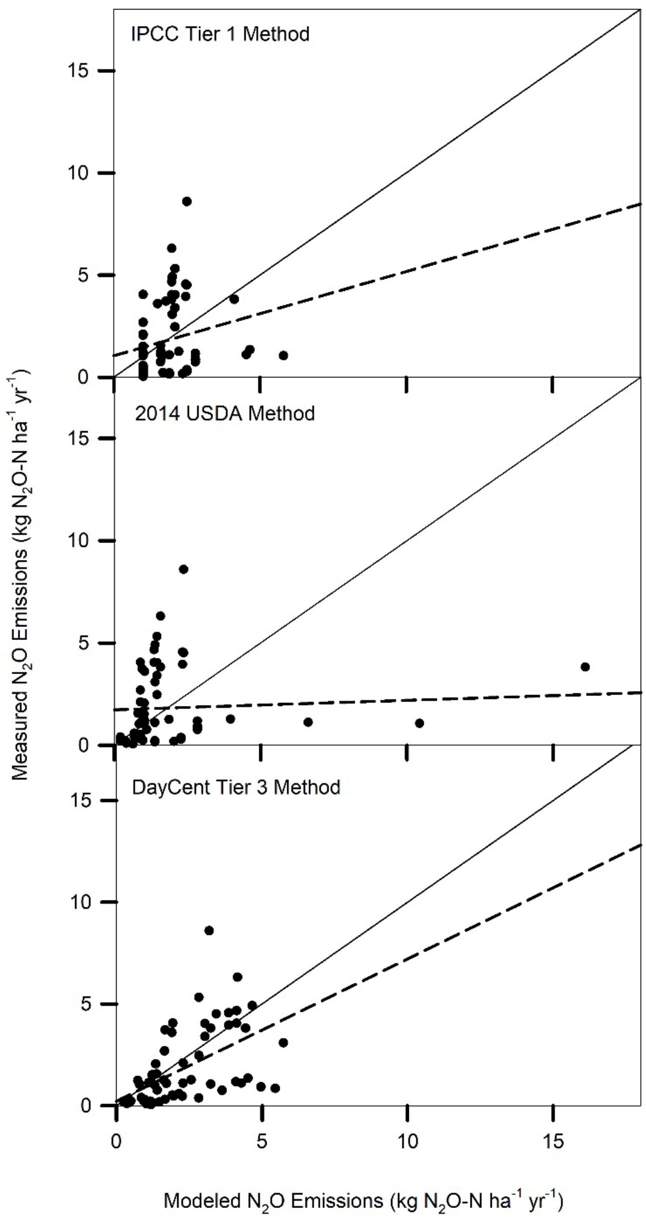
The fitted regression line for the DayCent model is closer to the reference line and has the lowest r^2 value for the fit to the observed emissions, followed by the IPCC method and the 2014 USDA entity-scale reporting method. Moreover, the fitted regression line for the 2014 USDA entity-scale reporting method has a relatively flat slope, which implies no relationship between observed and predicted emissions.

These comparisons show that the 2014 USDA entity-scale reporting method produces considerably higher estimates of soil N_2O emissions with higher fertilization rates, compared to the other two methods. This is not surprising given the goal to represent an exponential increase in N_2O emissions when N fertilization rates exceed the amount needed by the crop (Shcherbak et al. 2014). However, the method does not rank highest on any of the evaluation statistics. The IPCC method ranks the highest based on the mean square difference, but otherwise the DayCent model has the best fit to these data given the RMSE and regression fit.

The DayCent model was selected as the method for estimating soil N_2O emissions given the higher accuracy suggested by the regression fit. Furthermore, DayCent has been used for U.S. national reporting of soil N_2O emissions to the United Nations Framework Convention on Climate Change for more than a decade (e.g., U.S. EPA, 2020), and selecting this model ensures consistency between national and entity-scale reporting. Regardless, there is a need for further advances in modeling soil N_2O emissions is needed to improve accuracy in reporting of emissions, such as modeling of emissions associated with variation in fertilizer rates (e.g., Shcherbak et al. 2014), types of fertilizer, and timing of applications.

Table 3A-5. RMSE, Mean Difference, and Linear Regression Slope for Model Comparison to Observed Annual Emissions

Model	RMSE	Mean Difference	Regression Intercept	Regression Slope	r^2
IPCC Tier 1 method	104%	0.03	1.06	0.41	0.03
2014 USDA method	205%	0.32	1.72	0.04	< 0.01
DayCent Model	93%	0.48	0.22	0.70	0.28



The solid line is a reference for the 1:1 relationship in which the modeled and observed emissions would be equal. The dashed line is a linear regression fit showing the actual relationship between modeled and observed emissions. There are two additional estimates of N_2O emissions from the USDA method that are beyond 20 kg N_2O-N/ha/year and not included in the graph; none of the measured emissions exceed 10 kg N_2O-N/ha/year.

Figure 3A-2. Comparison of Modeled and Observed Annual N_2O Emissions for DayCent, IPCC, and 2014 USDA Entity-Scale Reporting Methods

The DayCent process-based model is the emissions estimator for most major commodity crops, grazing lands, and most soil types (figure 3A-2). The crops include alfalfa hay, barley, corn, cotton, grass hay, grass-clover hay, oats, peanuts, potatoes, rice, sorghum, soybeans, sugar beets, sunflowers, tobacco, and wheat. In addition, DayCent can be applied in most mineral soils, except very gravelly, cobbly, or shaley soils.[24] However, DayCent does not have the underlying model

[24] Classified as soils whose volume is more than 35 percent gravel, cobbles, or shale.

structure to estimate emissions for organic soils (i.e., *Histosols*), and the model has not been adequately tested and therefore is not currently applied to other crops and soil types. The IPCC Tier 1 method has been chosen for application in all other croplands and grazing lands to ensure that the method in this chapter provides a complete coverage of agricultural lands in the United States.

Adoption of DayCent as the primary model also allows for consistent simulation of carbon and nitrogen cycles for reporting of SOC stock changes and soil N_2O emissions (see section 3.2.4 for more information about the SOC methods). Carbon and nitrogen cycles are linked in plant-soil systems through biogeochemical processes of microbial decomposition and plant production (McGill and Cole, 1981); applying the same model to both sources ensures consistency in the treatment of the processes and the resulting carbon and nitrogen dynamics.

For the IPCC method, scaling factors estimated from available research are included for several specific management practices—slow-release fertilizers and nitrification inhibitors, no-till management, and biochar applications. The scaling factors enhance the ability of Tier 1 method to accurately estimate emissions, including capturing management practices that mitigate N_2O emissions from soils. The scaling factor for biochar applications is also applied to the DayCent model predicted N_2O fluxes.

3-A.3.2 Technical Documentation

Soil N_2O emissions are affected by specific farm management practices, particularly nitrogen management practices such as adding nitrification inhibitors or changing how, when, and where nitrogen fertilizers are applied. To account for the effect of management practices on N_2O emission, the DayCent process-based model represents the practices as part of its framework, such as routines to estimate the influence of slow-release polymer-coated fertilizers and nitrification inhibitors on soil N_2O emissions (Gurung et al. 2021).

In contrast, the IPCC Tier 1 method mainly addresses the effect of fertilizer rate on N_2O emissions, which is important but not the only impact of management on N_2O emissions. Consequently, management practice scaling factors were derived to allow for adjustments in the emissions and better represent the influence of key practices. Scaling factors were estimated from available research data. Management practices other than those included in the equation may also mitigate N_2O emissions, but data are currently insufficient to create generalized scaling factors. More data may lead to their inclusion in future updates to the method.

Offsite or indirect N_2O emissions, which occur when reactive nitrogen escapes to downwind or downstream ecosystems where favorable conditions for N_2O production exist, are even more difficult to estimate than direct emissions because there is uncertainty in both the amount of reactive nitrogen that escapes and the portion of this nitrogen that is converted to N_2O. Ideally, fluxes of volatile and soluble reactive nitrogen leaving the entity's parcel of land would be combined with atmospheric transport and hydrologic models to simulate the fate of reactive nitrogen. At present there are no linked modeling approaches sufficiently tested to be used in an operational framework. Consequently, the indirect N_2O emissions are calculated by applying IPCC Tier 1 indirect emission factors to the amounts of reactive nitrogen leached or volatilized (Hergoualc'h et al., 2019).

Similarly, direct N_2O emissions from drainage of organic soils are based on the IPCC Tier 1 methods (de Klein et al., 2006; Drösler et al., 2013). Although research is ongoing to provide improved emission factors and methods for estimating N_2O emissions from drainage of organic soils (Allen, 2012), more testing will be needed before they can be incorporated into an operational method. Future revisions to these methods will need to consider advancements.

3-A.4 Management Practice-Based Scaling Factors

Data were analyzed to derive scaling factors for the following practices: nitrification inhibitors, slow-release fertilizers, and biochar amendments. Scaling factors for nitrification inhibitors and slow-release fertilizers were derived using a linear mixed-effect modeling approach (Pinheiro and Bates, 2000), similar to the method used by Ogle et al. (2007) to derive factors that were used in the 2019 IPCC Guidelines (Ogle et al., 2019b). Variances associated with individual experimental results were not taken into consideration in the meta-analyses because many studies do not provide this information. A goal for future analyses supporting the USDA methods will be to include variances, under the assumption that studies will report this information in future publications. Covariates were included in the analysis to determine if the practice had a different effect depending on the land use, climate, soil type, water management, tillage practice, or crop type. Covariates were retained in the model if the variable was significant at an alpha level of 0.05. A 95-percent confidence interval was derived for each scaling factor and provided in table 3-17 as an upper and lower bound on the estimated factor.

The meta-analysis of biochar influence on N_2O emissions was based on a subset of the data from a recently published meta-analysis (Borchard et al., 2019), filtered to include only results from field experiments, i.e., excluding pot trials or incubations which are typically not representative of field conditions. These filtered data included a total of 112 field trials in 29 studies. Of these field trials, 41 treatments (from 13 studies) were a year or longer, and only 6 treatments from 2 studies were longer than 2 years. These data provide sufficient evidence to determine a significant ($p = 0.01$) effect over 1 year, and therefore, the impact is only estimated for the first year after application. More long-term field trials will be required before the longer term impact can be estimated with confidence for a GHG reporting method. Of the field trials, 32 percent were in rice, 34 percent in nonrice row crops, 5 percent were in grassland, and 30 percent in horticulture. We note that the effect size was the same in rice versus nonrice trials. The biochar field trial results were analyzed using robust variance estimations (Hedges et al., 2010) with random effects, including study as a random effect.

Documentation for the no-till scaling factor can be found in van Kessel et al. (2012). The studies used in each meta-analysis are provided below.

3-A.5 Meta-Analysis Studies

Nitrification Inhibitors

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3-A.6 Methane Flux for Nonflooded Soils

3-A.6.1 Rationale for Method

Agronomic activity typically reduces CH_4 uptake in cropland soils by 70 percent or more (Mosier et al., 1991; Robertson et al., 2000; Smith et al., 2000). This is a significant process influencing the concentration of CH_4 in the atmosphere. The chapter provides a Tier 3 method for CH_4 uptake in nonflooded mineral soils as defined by IPCC. For drained organic soils that are used for crop production or grazing, there may be no net flux annually or possibly a net emission of CH_4 to the atmosphere (Drösler et al., 2013; Tan et al., 2020). This guidance has adopted the IPCC Tier 1 method to estimate the CH_4 flux from drained wetlands (Drösler et al., 2013).

3-A.6.2 Technical Documentation

Soil CH_4 flux rates are affected by land use and environmental factors such as soil type, water content, and temperature. Among natural vegetation types, those dominated by woody vegetation have higher rates of CH_4 uptake than those characterized by herbaceous vegetation such as grassland. Conversion to cropland reduces the sink strength (Robertson et al., 2000; McDaniel et al., 2019). The CH_4 flux rates and attenuation of those rates depend on the land use and were derived from previous published studies.

Average CH_4 flux rates for natural vegetation are derived from a dataset compiled by Del Grosso et al. (2000) combined with McDaniel et al. (2019). Studies selected met two criteria: (a) day of the year was provided in the study, and (b) measurements were made for more than 1 month. There were 13 sites with 1,600 observations for grassland and 6 sites with 80 observations for forest land that met these criteria. A linear mixed-effect model was fit using daily observations, with day of year and climate as potential fixed effects, and a random effect of site. The model also included a quadratic term of day of year to capture seasonal patterns. For model parsimony and simplicity in estimating uncertainty, separate models were derived for forest and grassland. For forestland, there appeared to be differences in fluxes between forest in dry versus wet climates; however, with limited studies in dry forests the difference was not significant at the 0.05 alpha level. Almost all of the grassland sites occurred in dry climates so this variable was not tested in the grassland model. To estimate an overall flux rate, the linear mixed-effect model was applied to estimate fluxes for each day of the year and then summed to produce the annual fluxes. Uncertainty is associated with the model parameters and random effect for site.

Management factors are scalars that are used to adjust the methane flux from the natural vegetation for annual cropland management. Response ratios were derived by dividing the methane flux for annual cropland management by the methane flux for native vegetation. A linear mixed-effect model could not be developed for the management factors due to limited studies comparing annual cropland to forest land and grassland. Instead, the estimated impact of annual cropland management was based on the average of the site level response ratios, along with the standard deviation of the ratios to derive a probability density function for error propagation. Data for conversion from natural vegetation to perennial cropland were also analyzed, but no clear patterns were apparent. Therefore, management factor for conversions from natural vegetation to perennial cropland are assumed to be negligible and a factor value of 1 is assigned in the calculation.

Drained wetlands will tend to have no net flux or emissions of CH_4 following conversion to cropland or grazing land (Drösler et al., 2013; Tan et al., 2020). The CH_4 emission factors for drained wetlands are from the *2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands* (Drösler et al., 2013).

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3-A.7 Methane Emissions From Flooded Rice Cultivation

3-A.7.1 Rationale for Method

The methods were chosen to minimize uncertainty. They differ from U.S. EPA (2020) inventory methods which do not currently account for recent research in the United States used in the development of a Tier 2 method (Linquist et al., 2018) for specific regions of the Mid-South and California (see figure 3-5). The country-specific factors derived from this study provide more accurate estimates of emissions than Tier 1 methods. There are a number of other possibilities for estimating GHG emissions from flooded rice systems. Notably, process-based models, which are considered Tier 3 methods, can be used to quantify GHG emissions, such as the DNDC (e.g., Zhang et al., 2011) and DayCent models (Cheng et al., 2013). It is anticipated that process-based models may be further tested and calibrated at entity scales across the United States and possibly adopted for application in a future version of these methods.

3-A.7.2 Technical Documentation

Linquist et al. (2018) developed the basis for the Tier 2 method in this report. This method is applied to counties with rice production in the 2016 NASS Crop Data Layer, which includes counties in Arkansas, California, Louisiana, Mississippi, Missouri, and Texas. Additionally, counties that were within two counties of the originally identified rice production counties were included in the Tier 2 method. In any State that had more than 80 percent of its counties identified, the entire State was included in the Tier 2 method. In summary, Tier 2 methodology can be used in all counties in California, Arkansas, Louisiana, and Mississippi and select counties in Missouri and Texas (see figure 3-5 and table 3A-6.).

Table 3A-6. Counties in Texas and Missouri That Use the Tier 2 Methodology

Missouri	Barry, Bollinger, Butler, Cape Girardeau, Carter, Christian, Crawford, Dent, Douglas, Dunklin, Franklin, Gasconade, Howell, Iron, Jefferson, Lawrence, Lincoln, Madison, McDonald, Mississippi, Montgomery, New Madrid, Newton, Oregon, Ozark, Pemiscot, Perry, Phelps, Pike, Reynolds, Ripley, Scott, Shannon, St. Charles, St. Francois, St. Louis, St. Louis, Ste. Genevieve, Stoddard, Stone, Taney, Texas, Warren, Washington, Wayne
Texas	Anderson, Angelina, Aransas, Atascosa, Austin, Bastrop, Bee, Bell, Bexar, Blanco, Bosque, Bowie, Brazoria, Brazos, Brooks, Burleson, Burnet, Caldwell, Calhoun, Cameron, Camp, Cass, Chambers, Cherokee, Collin, Colorado, Comal, Cooke, Coryell, Dallas, Delta, Denton, DeWitt, Duval, Ellis, Erath, Falls, Fannin, Fayette, Fort Bend, Franklin, Freestone, Frio, Galveston, Goliad, Gonzales, Grayson, Gregg, Grimes, Guadalupe, Hamilton, Hardin, Harris, Harrison, Hays, Henderson, Hidalgo, Hill, Hood, Hopkins, Houston, Hunt, Jackson, Jasper, Jefferson, Jim Hogg, Jim Wells, Johnson, Karnes, Kaufman, Kenedy, Kleberg, La Salle, Lamar, Lampasas, Lavaca, Lee, Leon, Liberty, Limestone, Live Oak, Llano, Madison, Marion, Matagorda, McLennan, McMullen, Medina, Milam, Montgomery, Morris, Nacogdoches, Navarro, Newton, Nueces, Orange, Palo , into, Panola, Parker, Polk, Rains, Red River, Refugio, Robertson, Rockwall, Rusk, Sabine, San Augustine, San Jacinto, San Patricio, San Saba, Shelby, Smith, Somervell, Starr, Tarrant, Titus, Travis, Trinity, Tyler, Upshur, Van Zandt, Victoria, Walker, Waller, Washington, Wharton, Willacy, Williamson, Wilson, Wise, Wood, Zapata

Baseline emission factors for the Tier 2 method represent standard practices for the two primary rice production regions in the United States, namely the Mid-South (Arkansas, Louisiana, Mississippi, Missouri, and Texas) and California. Studies from these 2 regions were analyzed and included 27 observations from 17 studies in the Mid-South and 13 observations from 7 studies in California (Linquist et al., 2018). Standard practices in the Mid-South include rotating rice with low-residue-producing crops, drill seeding (continuously flooded from 3-6 leaf stage to final drain), no organic amendment, and no sulfur amendment. Standard practices in California include continuous rice (i.e., no crop rotation), straw incorporation and winter flooding, water seeding, no organic amendment, and no sulfur amendment. Average seasonal CH_4 emissions for the baseline conditions were 194 kg CH_4/ha/season in the Mid-South and 218 kg CH_4/ha/season in California (Linquist et al., 2018). The percent of clay in soils was found to have a significant impact on the emissions and is used to adjust the daily baseline emission factor.

Differences in CH_4 emissions between the baseline and other management practices are estimated with scaling factors to adjust the baseline emission factor for the effects of other water management practices other than continuous flooding (during the cultivation period), sulfur amendments, residue amounts, and seeding method (California only). All rice in the United States is irrigated, and drydown events have been found to influence CH_4 emissions (Linquist et al., 2018). The scaling factors of single and multiple aerations differ from each other but are the same for both geographical regions (Linquist et al., 2018). The scaling factor used to estimate the effect of sulfur amendments varies depending on the amount of sulfur added. For every 30 kg S/ha added, CH_4 emissions are reduced by 4 percent (Linquist et al., 2018).

Residue left in the field from a previous crop can increase CH_4 emissions during the production season because residue provides carbon substrate for methanogenesis during the flooded season (Yan et al., 2005). The two rice growing regions in the Tier 2 method have different baseline residue managements. In the Mid-South, a typical rotation would include a year of a low-residue crop such as soybeans prior to rice. Soybeans leave less residue and decompose at a faster rate than cereal residues (Xu et al., 2017). A deviation from the baseline management with rice production followed by another season of rice in the Mid-South was found to increase CH_4 by 116 percent, which is a scaling factor of 2.16 (Linquist et al., 2018). In California, baseline management includes rice residue incorporation after harvest and then flooding. A low-residue crop would be a deviation from the baseline of a relatively high-residue production crop, such as rice, and would decrease CH_4 by 54 percent or a scaling factor of 0.46 (Linquist et al., 2018). Differences in rotation practice influence emissions in both regions—but in the opposite direction because the typical rotation in California is to have a relatively high-residue crop before rice, while in the Mid-South it is more common to have a low-residue crop before rice production in a rotation.

Water seeding is the typical method for planting in California, representing the standard baseline condition. However, drill seeding is another option and will reduce CH_4 emissions, on average, by 60 percent, which is a scaling factor of 0.40 (Linquist et al., 2018). The scaling factor for seeding method in California can only be applied if the scaling factor for litter conditions is equal to 1. Limited data are available on water seeding impact on CH_4 in the Mid-South; it is likely an uncommon practice in the region.

3-A.8 Carbon Dioxide From Liming

3-A.8.1 Rationale for Method

Addition of carbonate limes to soils, i.e., limestone and dolomite, is typically thought to generate CO_2 emissions to the atmosphere (de Klein et al., 2006), but prevailing conditions in U.S. agricultural lands lead to some CO_2 uptake because a significant amount of lime is dissolved in the presence of H_2CO_3. A method developed by West and McBride (2005) addresses these dynamics and has been adopted for the reporting of CO_2 emissions from carbonate lime applications in the United States. This method is also used by the U.S. EPA for national-scale reporting of CO_2 emissions from agricultural lands (U.S. EPA, 2020).

3-A.8.2 Technical Documentation

The country-specific factors are based on a study by West and McBride (2005). Since $CaCO_3$ contains 12 percent carbon, an application of 1 kg $CaCO_3$ contains 0.12 kg carbon. It is assumed that 62 percent (0.8 kg) of carbonate lime dissolution occurs in presence of carbonic acid, generating HCO_3- and removing 0.27 kg CO_2-C from the atmosphere. The remaining 38 percent (0.4 kg) of the dissolution occurs in the presence of nitric acid and generates 0.17 kg CO_2-C emissions to the atmosphere. The amount of lime dissolution by carbonic vs. nitric acid is highly uncertain, ranging from 24 to 100 percent dissolution with carbonic acid. Approximately half of the calcium ions released in this reaction are leached through the soil profile, although this value is highly uncertain and can range from nearly 0 to 100 percent. Leaching of calcium and other cations removes HCO_3- and other anions from the soil profile. The HCO_3- ions remaining in the profile will lead to an emission of 0.27 kg CO_2-C to the atmosphere. There is also precipitation of calcium carbonate in the ocean margin, leading to an emission of 0.05 kg CO_2-C to the atmosphere. The net balance is 0.22 kg CO_2-C of emissions, or 0.059 kg CO_2 per 1 ton of crushed of limestone applied to soils.

This method makes similar assumptions about the fate of dolomite. Since crushed dolomite ($MgCa(CO_3)_2$) contains 13 percent carbon, an application of 1 kg $CaCO_3$ contains 0.13 kg C. Dolomite lime dissolution is assumed to have the same proportion as crushed limestone, which is 62 percent (0.8 kg) in the presence of carbonic acid, generating HCO_3- and removing 0.30 kg CO_2-C from the atmosphere. The remaining 38 percent (0.4 kg) of the lime is dissolved in the presence of nitric acid, generating 0.18 kg CO_2-C of emissions to the atmosphere. As with crushed limestone, this method assumes that approximately half of the calcium and magnesium ions released in this reaction are leached through the soil profile with HCO_3- and other anions, but this is highly uncertain, ranging almost from 0 to 100 percent. There will be an emission of 0.30 kg CO_2-C to the atmosphere associated with the remaining HCO_3- in the soil. There is also precipitation of calcium carbonate in the ocean margin, leading to an emission of 0.05 kg CO_2-C to the atmosphere. The net balance is 0.235 kg CO_2-C of emissions, or 0.064 kg CO_2 per 1 ton of crushed of limestone applied to soils.

3-A.9 Non-CO_2 Emissions From Biomass Burning

3-A.9.1 Rationale for Method

Non-CO_2 GHG emissions from biomass burning include CH_4 and N_2O. Carbon monoxide and NO_x are also emitted and are precursors of GHGs (i.e., release of these gases leads to GHG formation elsewhere). Carbon dioxide is also emitted but is not addressed for crop residue or grassland burning because the carbon is reabsorbed from the atmosphere in new growth of crops or grasses within an annual cycle. However, CO_2 emissions are estimated for trees in agroforestry, tree crops, and shrubs by calculating the loss of woody biomass using methods in section 3.2.1.

There has been limited development and testing of models or empirical methods for estimating non-CO_2 GHG emission from U.S. biomass burning. Consequently, country-specific data are limited on the amount of non-CO_2 GHG emissions that could be used to derive country-specific emission factors for a Tier 2 method. Therefore, this guidance has adopted the IPCC Tier 1 method as described by Aalde et al. (2006).

3-A.9.2 Technical Documentation

See Aalde et al. (2006) for the technical documentation on this method.

3-A.10 CO_2 From Urea Fertilizer Applications

3-A.10.1 Rationale for Method

Urea fertilizer application to soils contributes CO_2 emissions to the atmosphere. The CO_2 incorporated into the urea during the fertilizer production process comes from fossil fuel sources in the U.S. fertilizer plants. The CO_2 captured during the production process is considered an emissions removal in the manufacturer’s reporting, so its release following urea fertilization on soils is reported by the entity managing the cropland or grazing land. If manufacturers do not estimate CO_2 capture during urea production and include the recaptured CO_2 as an emission, there is no need for a farm-scale entity to report release.

The Tier 1 method has been adopted from IPCC guidelines (de Klein et al., 2006). No other methods have been developed or tested sufficiently, and there are insufficient measurement data to derive a country-specific emission factor.

3-A.10.2 Technical Documentation

See de Klein et al. (2006) for the technical documentation on this method.

Appendix 3-B: Summary of Research Gaps for Cropland and Grazing Land Management

This appendix discusses research gaps associated with cropland and grazing land management impacts on soil carbon stock changes and GHG emissions. The list is not necessarily exhaustive but highlights some key gaps that will need further research before there is sufficient evidence for additional criteria to be included in the methodology. In general, most prior experimental efforts have focused on components of GHGs, but few studies have been conducted on total GHG budgets to include CO_2, N_2O, and CH_4 in combination, which is needed to quantify interacting effects on the net emissions of these gases (Liebig et al., 2010). In addition, limited research has been conducted to address the influence of catastrophic weather events on GHG emissions, such as major floods, tornadoes, and hurricanes.

3-B.1 Biomass Carbon Stock Changes

The following data collection would improve the estimation of woody trees in agroforestry and perennial crop system.

- More data on allometric relationships for woody species grown in open environments including agroforestry and perennial woody crop systems.

3-B.2 Soil Carbon Stocks

The following processes and practices require further study to improve fundamental understanding or fill data gaps in the carbon inventory methods.

- Improved mechanistic understanding and ability to quantify the fate of SOC with transport and sedimentation following erosion events;
- Improved mechanistic understanding of soil carbon dynamics in the subsoil horizons to extend methods for estimating SOC stock changes in mineral soils below a 30 cm depth;
- Further research on the variation in types and residence times of biochar amendments in different soils and climates, in addition to biochar impact on other GHG emissions (N_2O and CH_4), priming of soil organic matter decomposition, crop growth, inorganic carbon, and the movement of biochar in the landscape over time;
- Further research on management impacts influencing soil C stocks in specialty crop systems;
- Further research evaluating the impact of enhancing rock weathering (e.g., amending soils with powdered basalt) on agricultural production and the environment, as well as development of methods to quantify the removal rate for CO_2;
- Data on long-term responses of SOC to variation in stocking rate, grazing method (i.e., continuous, rotational, short-duration rotational, ultra-high stocking density, and adaptive management approaches), and vegetation composition (i.e., forb and grass mixtures, cool- and warm-season grass mixtures, grass and legume mixtures, grass and woody mixtures, and plant architecture types), and whether these responses are mediated by different soil types, climatic conditions, botanical compositions, grazing methods, fertilizer regimes, and other factors;

- Improved ability to quantify the influence of agroforestry, woody plant encroachment, and perennial woody crops on SOC stocks;
- Improved modeling of SOC dynamics as the process-basis for the formation and fate of soil organic matter is better understood through both experimental field and laboratory research and incorporated into models;
- Expanded monitoring of SOC stocks and stock changes in croplands and grazing lands, such as a national monitoring network with repeated sampling of SOC stocks at permanent locations (e.g., Spencer et al., 2011). The observational data could be used to inform model selection and parameterization as part of a system for entity- and national-scale reporting of SOC stock changes and GHG emissions in the United States (e.g., Ogle et al., 2020);
- More studies to determine the net impact of agricultural management on GHG emissions with experiments measuring SOC stocks combined with other GHGs, particularly N_2O and CH_4. These studies could even be expanded to address other impacts of agriculture such as nutrient leaching and other gaseous losses that can affect water and air quality;
- More research on the interactions between animals and livestock with the cropland and grazing land management systems, including how interdependent factors such as forage quality, maturity, total intake, and supplemental feeds impact both animal emissions and soil emissions/fluxes.

3-B.3 Soil Nitrous Oxide Emissions

The following practices have, in some studies, significantly affected N_2O emissions, but need additional research across different soil types and climate:

- Development of a set of geographically stratified experimental sites at which factors known to affect agronomic N_2O emissions could be tested in the context of different management systems;
- Capacity of spatially precise fertilizer application technology (variable rate applicators) to lower N_2O fluxes (both direct and indirect) and increase NUE;
- Further study of the effect of pressurized and nonpressurized irrigation systems on soil N_2O emissions;
- Further research on management impacts influencing soil N_2O emissions in specialty crop systems;
- Effects of banded nitrogen fertilizer applications, shown in some studies to increase NUE and in others to increase N_2O emissions;
- Further evaluation of fertigation effects on soil N_2O emissions and other N losses leading to indirect N_2O emissions;
- The generalizability of different fertilizer formulations on N_2O emissions, in particular for urea vs. anhydrous ammonia vs. injected solutions;
- Long-term experiments, particularly field trials, quantifying impact of biochar amendments, tillage, cover crops, irrigation, manure amendments and other cropland management practices on soil N_2O;
- More research on the responses of soil N_2O emissions to variations in stocking rates, grazing methods (continuous, rotational, short-duration rotational, and ultra-high stocking density), and vegetation composition (forb and grass mixtures, cool- and warm-season grass

mixtures, grass and legume mixtures, grass and woody mixtures, and plant architecture types), both individually and in combinations; and

- Improved estimates of indirect emissions, and in particular the percentage of nitrogen that is lost from a field through volatilization or leaching/runoff and later converted to N_2O in downstream and downwind ecosystems. Additional study on practices that can reduce NO_3- losses as well as practices that can reduce NH3 and NOx losses.

Research is also needed to improve modeling and empirical quantification of soil N_2O emissions in order to provide estimates of N_2O fluxes that integrate multiple management practices simultaneously:

- Further development and validation of quantitative simulation models predicting N_2O fluxes in response to differing management practices, with particular respect to rate, timing, placement, and formulation of added fertilizers, both synthetic and organic; irrigation method (pressurized and nonpressurized systems); tillage type and intensity; residue management; fertigation; and biochar amendments;
- Conducting model inter-comparisons to accelerate the development of the next generation of models, by comparing various representations of processes that drive N_2O emissions and identifying superior approaches for estimating emissions and incorporating those methods into new models;
- More data on seasonal and annual N_2O emissions, including emissions during the non-growing season and in particular winter and freeze-thaw periods;
- Development of standardized methodologies and creation of new technologies for rapid assessment of N_2O fluxes in the field while also improving quantification of spatial and temporal variation of N_2O emissions in different cropping systems and landscapes to provide a more accurate assessment of seasonal and annual emissions;
- Better understanding of the sources of N_2O in soils (e.g., nitrification vs. denitrification) and consequences for feedbacks among adaptive management, soil physical and biological attributes, and SOC dynamics; and
- Long-term monitoring of N_2O emissions on a statistically based sample of farms throughout the United States to support model calibration and reduce uncertainty in estimated emissions from croplands and grazing lands (Ogle et al., 2020). This network could be combined with atmospheric N_2O concentration data and inverse model predictions of N_2O fluxes to further constrain and reduce uncertainty in emission predictions.

3-B.4 Methane Flux in Nonflooded Soils

Soil CH_4 flux in nonflooded soils is typically dominated by uptake and it is known to decrease by about 70 percent upon conversion of long-standing natural vegetation to agricultural management (Mosier et al., 1991; Robertson et al., 2000; Smith et al., 2000; McDaniel et al., 2019). However, CH_4 flux rates for soils under natural vegetation are not well known for all climates and soils, so additional measurements would be useful to reduce uncertainty in the method. Moreover, additional research is needed to further evaluate the impact of perennial cropland management on methane fluxes.

Further development and testing of process-based simulation models capable of accurately predicting CH_4 fluxes for nonflooded soils would also be an improvement. Process-based models would likely better generalize effects and possibly improve assessments that evaluate the enhancement of sink potential of cropland and grazing land soils for reducing greenhouse gas concentrations in the atmosphere. Furthermore, there is limited research on the effect of grazing land management on CH_4 oxidation, although variation in stocking rates, grazing methods, and associated practices may have an influence on CH_4 fluxes from nonflooded soils.

3-B.5 Flooded Rice Cultivation

The transition from rice CH_4 emissions calculations based on Asian systems to those based on U.S. systems is an important step forward in this version of the methods report. Contrary to Asian systems, U.S. systems use a single growing season followed by a distinct winter season vs. multiple crop seasons per year, direct or water seeding vs. transplanting, a high degree of mechanization, larger land holdings, and different cultivars. The research underlying the Tier 2 method were all from U.S. studies published on or before 2014 and found in Linquist et al. (2018). However, Linquist et al. identified gaps that require further research:

- Improved understanding of ratoon cropping and strategies to reduce emissions from these systems;
- The impacts of additional seeding method on emissions, specifically water seeding in regions that are dominated by drill seeding;
- Research on rice varietal effects on emissions (While many studies have shown varietal differences in how much CH_4 is emitted, the challenge is that by the time these differences are understood, the variety may no longer be widely used); and
- Improved understanding of how multiple practices influence emissions.

All data presented in Linquist et al. (2018) were used to quantify scaling factors, leaving no validation data to test the scaling factors. New studies published since 2014 (Balaine et al., 2019; Kongchum et al., 2020; Reba et al., 2019; Runkle et al., 2019) provide additional opportunity to improve scaling factors and provide validation.

Furthermore, more research is needed to further calibrate process-based models and evaluate their performance. DayCent is currently used to estimate CH_4 emissions in the U.S. GHG Inventory (U.S. EPA, 2020), but more testing is needed before it can be used for finer-scale estimation of CH_4 emissions from rice production on land parcels.

Until recently, emissions data for rice systems were generated using chamber studies. Recent studies using eddy covariance (EC) equipment are now available (Reba et al., 2019; Runkle et al., 2019). EC systems allow for an automated, field-integrated measure of the flux of interest, but are restricted to larger field sizes. As such, EC systems are typically deployed on farms in collaboration with producers rather than on experiment stations. Fluxes that are measured with EC systems typically include CO_2, H_2O, and CH_4 in rice. Recent developments in N_2O devices using EC show promise for including this trace gas in future research efforts. Improving our understanding of these different collection methods is an area where more research is needed.

The following practices have significantly affected CH_4 or N_2O emissions but require further side-by-side comparisons with experimental designs across different soil types and climates within the United States to further refine scaling factors and improve modeling efforts.

- It is well known that rice straw management and winter flooding influences CH_4 emissions. However, further study is needed to reduce uncertainty in emission rates for the precultivation period.

- Limited data on nitrogen placement suggests that deep placement of fertilizer reduces CH_4 emissions. However, more research is needed to confirm the findings to determine differences in emissions due to fertilizer placement.

Appendix 3-C: GHG Emissions Intensity

GHG emissions intensity (GHGI) is another metric for evaluating trends in emissions related to production. A GHGI metric incorporates production data to quantify the amount of emission per unit of production. One may work towards lowering GHGI via several pathways, including reducing GHG emissions, enhancing carbon stocks, or increasing production relative to the amount of GHG emissions (note that increasing production may not always decrease emissions).

Equation 3C-1 shows a method for estimating a partial GHGI metric accounting for annual emissions arising within an individual land parcel. Emissions may then be aggregated across all parcels.

Equation 3C-1: GHGI Metric

$$GHGI = (\Delta C_{biomass} + \Delta TC_{mineral} + \Delta C_{organic} + N_2O_{direct} + N_2O_{indirect} + CH_{4nfms} + CH_{4dos} + CH_{4rice} + \Delta C_{lime} + GHG_{biomassburning} + C_{urea}) \div Y$$

Where:

$GHGI$	=	greenhouse gas emissions intensity (metric tons CO_2-eq/metric tons dry matter crop yield, metric tons CO_2/kg carcass yield, metric tons CO_2/kg fluid milk yield from the entity's operation)
$\Delta C_{biomass}$	=	total annual change in biomass carbon stock (metric tons CO_2-eq)
$\Delta TC_{mineral}$	=	annual change in mineral soil organic carbon stock plus biochar amendments (metric tons CO_2-eq)
$\Delta C_{organic}$	=	annual CO_2 equivalent emissions from soil organic carbon change in organic soils, i.e., *Histosols* (metric tons CO_2-eq)
N_2O_{direct}	=	annual direct soil N_2O emissions for land parcel (metric tons CO_2-eq)
$N_2O_{indirect}$	=	annual indirect soil N_2O emissions (metric tons CO_2-eq)
CH_{4nfms}	=	CH_4 flux for nonflooded mineral soils (metric tons CO_2-eq)
CH_{4dos}	=	CH_4 flux for drained organic soils (metric tons CO_2-eq)
CH_{4rice}	=	annual CH_4 emissions from rice cultivation (metric tons CO_2-eq)
ΔC_{lime}	=	annual change in soil carbon stocks from lime application (metric tons CO_2-eq)
$GHG_{biomassburning}$	=	annual emissions of GHGs or precursors due to biomass burning (metric tons CO_2-eq)
C_{urea}	=	annual release of carbon from urea added to soil (metric tons CO_2-eq)
Y	=	total yield of crop (metric tons dry matter crop yield/year), meat (kg carcass yield/year) or milk production (kg fluid milk yield/year)

A full GHG intensity calculation is beyond the scope of this chapter. Such a calculation could include life cycle emissions related to provision of energy and materials imported into the production system, including for example, production of fertilizer, other agrichemicals, organic amendments, seed, machinery, and irrigation water, as well as on-farm energy use. The GHGI can also be estimated with emissions data from animal agriculture and forestry-related activities if those are included within the operation. However, it is important to note that only one product can be evaluated in a single estimation, unless the products are converted into a unit of equivalency, such as caloric content, or emissions are allocated to the various products in proportion to their economic value. This metric produces complementary information to the absolute emission data that may be incorporated into management and policy plans.

Chapter 4
Quantifying Greenhouse Gas Sources and Sinks in Animal Production Systems

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Acronyms, Chemical Formulae, and Units

3-NOP	3-nitrooxypropanol
ADF	acid detergent fiber
ASABE	American Society of Agricultural and Biological Engineers
B_0	maximum methane production capacity
bLS	backward Lagrangian stochastic
BW	body weight
CH_4	methane
CO_2	carbon dioxide
CO_2-eq	carbon dioxide equivalents
CP	crude protein
CSTR	continuous stirred tank reactor
DE	digestible energy
DFM	direct-fed microbials
DGS	distillers grains with solubles
DM	dry matter
DMI	dry matter intake
EE	ether extract
EF	emission factor
g	gram
GEI	gross energy intake
GHG	greenhouse gas
GWP	global warming potential
IPCC	Intergovernmental Panel on Climate Change
kg	kilogram
lb(s)	pound(s)
LCA	life cycle analysis
LU	livestock unit
m	meters
MCal	megacalorie
MCF	methane conversion factor
MF	milk fat concentration
mg	milligram
MGA	melengestrol acetate
MJ	megajoule
N	nitrogen
N_2O	nitrous oxide
NDF	neutral detergent fiber
NE	net energy
N_{ex}	nitrogen excretion
NFC	nonfiber carbohydrate
NH_3	ammonia
O_2	oxygen
ppm	parts per million
RDP	ruminal degradable protein
RMSPE	residual mean square prediction error

SF_6	sulfur hexafluoride
TDN	total digestible nutrients
UASB	upflow anaerobic sludge blanket
U.S. EPA	U.S. Environmental Protection Agency
VS	volatile solids
Y_m	methane conversion factor: percent of gross energy in feed converted to methane

4. Quantifying Greenhouse Gas Sources and Sinks in Animal Production Systems

This chapter provides methodologies and guidance for reporting greenhouse gas (GHG) emissions associated with entity-level fluxes from animal production systems. It focuses on methods for estimating emissions from dairy cattle, beef cattle (cow-calf, stocker, and feedlot systems), sheep, swine, and poultry (e.g., layers, broilers, and turkeys). This chapter summarizes animal management practices and their associated GHG emissions, then describes the methods for estimating GHG emissions from enteric fermentation, housing, and manure management. This chapter and its appendixes provide insight into the current state of the science and serves as a starting point for future assessments:

- Section 4.1 provides the background to the emissions discussion, interactions, and boundaries for the methods.
- Section 4.2 provides the methods for estimating GHGs from enteric fermentation (resulting from animal digestive processes).
- Section 4.3 provides the methods for estimating GHGs from housing.
- Section 4.4 provides the methods for estimating GHGs from manure management systems, including solid manure storage, composting, aerobic lagoons, anaerobic lagoons or other liquid systems, and anaerobic digestion.

This chapter has six appendixes:

- Appendix 4-A provides overviews of dairy cattle, beef cattle, sheep, swine, and poultry production systems and background information related to enteric fermentation, housing, and manure management emissions.
- Appendix 4-B provides the rationale and technical documentation for the methods. It includes discussion on data gaps for uncertainty quantification.
- Appendix 4-C summarizes research gaps for estimating GHG emissions in animal production systems that could provide a basis for future development of the methods presented in this chapter.
- Appendix 4-D discusses management factors not used in adjusting the methane conversion factor (Y_m) for feedlot cattle but that affect GHG emissions per unit of production in feedlot cattle.
- Appendix 4-E provides information on nutritional content of animal feedstuffs (Dairy One, 2021; Ewan, 1989; NASEM, 2016; Preston, 2013).
- Appendix 4-F provides relevant equations and tables from IPCC (2019) to assist with calculations.

4.1 Overview

This section describes the key practices in animal management and the resulting GHG emissions that are discussed in detail in this chapter. The agricultural practices discussed include those required to breed and house animals, along with the management of the resulting manure.

This section also discusses options for management changes that may result in changes in GHG emissions.

4.1.1 Description of Sector

Animal production systems include agricultural practices that involve breeding and raising animals for meat, eggs, milk, and other animal products such as leather, wool, fur, and industrial products like glue or oils. Animals considered in this sector include cattle, swine, and poultry, along with other animals such as sheep, goats, American bison, llamas, alpacas, deer, horses, mules and asses, rabbits, and fur-bearing animals.

Farmers and other facility owners raise animals in either confined, semi-confined, or unconfined spaces. They also use different practices to raise the animals, depending on animal type, region, land availability, and individual preferences (e.g., conventional or organic standards). See appendix 4-A for more background information on animal production systems.

The magnitude of GHG emissions from animal management depends primarily on the quality of the diet, the animals' physiological status and nutrient requirements (e.g., grazing, pregnant, lactating, doing work), feed intake, and the systems in place to house animals and manage manure.

This chapter considers the following manure storage and treatment practices:

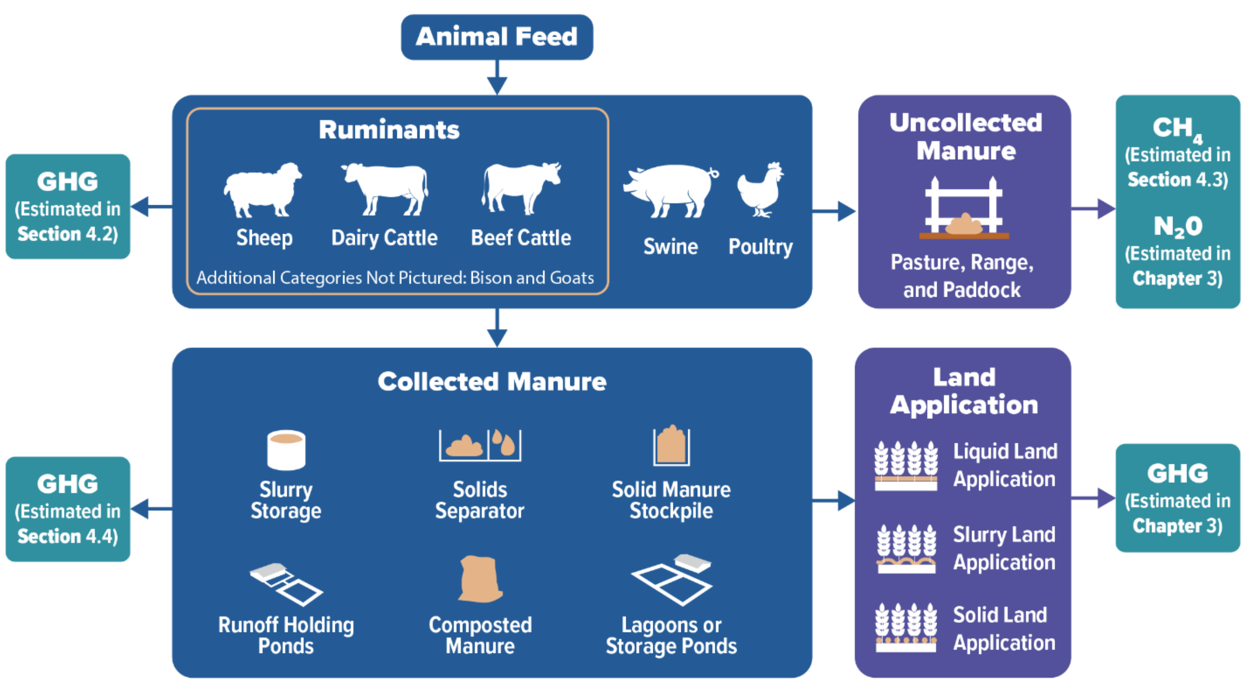
Solid manure:

- Temporary stack and long-term stockpile
- Composting

Liquid manure:

- Aerobic lagoons
- Anaerobic lagoons/runoff holding ponds/storage tanks
- Anaerobic digestion

Figure 4-1 provides an overview of the connections between feed, animals, manure, and GHG emissions in an animal production system.



Note: See section 4.5 for land application inputs to chapter 3, if applicable.

Figure 4-1. Connections Between Feed, Animals, Manure, and GHG for Animal Agriculture

4.1.2 Resulting GHG Emissions

The primary GHG emissions from animal production systems are CH_4 and N_2O. The emission of ammonia (NH_3) from manure and leaching of manure N from housing and storage also contribute to indirect N_2O emissions when this N is either deposited in the landscape or transferred to surface waters. Figure 4-2 generally depicts these sources and their interactions. This chapter divides methods for estimating GHG emissions into three categories: emissions from enteric fermentation, emissions from housing, and emissions from manure management systems. The housing category includes GHG emissions from manure deposited in the housing unit and manure that is managed inside those areas (such as interior stockpiles). The manure management category includes GHG emissions from manure handling, treatment, and storage.[1]

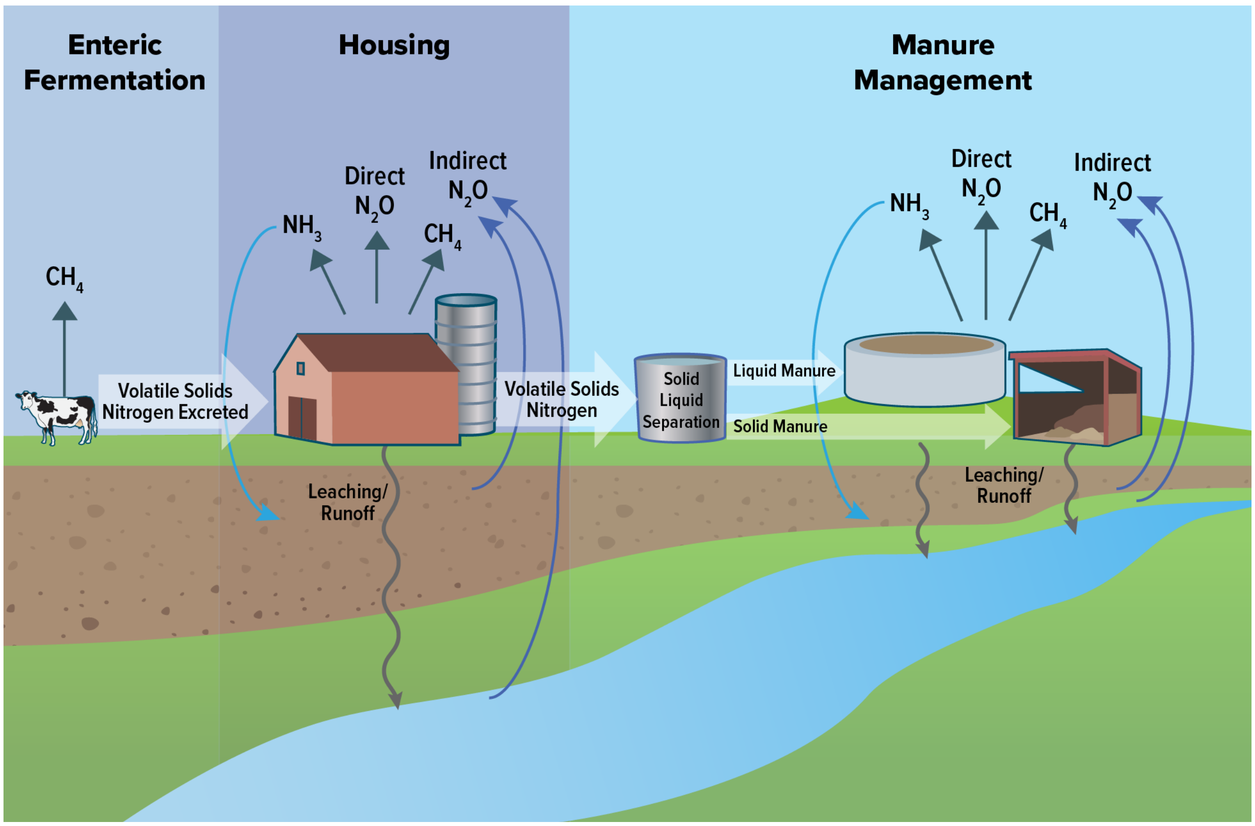


Figure 4-2. Animal Production Emission Sources and Interactions

The main source of CH_4 emissions from ruminant animal production systems is enteric fermentation, which is the result of normal bacterial fermentation as ruminant animals digest feed. Nonruminant animals such as swine also emit CH_4 through their digestive processes, but significantly less than ruminant animals do (~2.3 percent of total enteric CH_4 emissions in the United States). For simplicity, this chapter uses enteric fermentation to refer to CH_4 emissions from the digestive process of both ruminant and nonruminant animals.

The largest source of N_2O emissions—and, in some cases, a significant source of CH_4 emissions—is the management of animal manure. Manure management is the collection, storage, transfer, and treatment of animal urine and feces. Storage of animal manure has become increasingly popular: it

[1] Emissions from manure deposited on grazing lands are addressed in chapter 3, "Croplands and Grazing Lands."

allows synchronization of land application of manure nutrients with crop needs, reduces the need for purchased commercial fertilizer, and reduces potential for soil compaction due to poor timing of manure application. Direct N_2O emissions occur via combined nitrification and denitrification of nitrogen in the manure; indirect emissions result from volatile nitrogen losses, mainly in the forms of NH_3 and nitrogen oxides (IPCC, 2019). This chapter considers both direct and indirect emissions; total emissions are the summation of these sources.

The methodology used to estimate emissions from manure and bedding in housing is similar to the method described for manure handling and storage systems. Manure generated by animals, along with bedding used in some systems, may release N_2O and CH_4 into the atmosphere during the decomposition process. Manure from grazing animals is left on fields or paddocks. Manure from dry lots and barns may be collected to be treated, stored, and applied to croplands. Methane emissions from grazing lands are covered in the housing section (section 4.3), while N_2O emissions from manure deposited on grazing lands and croplands are addressed in chapter 3.

4.1.2.1 Enteric Fermentation Emissions

CH_4-producing microorganisms, called methanogens, exist in the gastrointestinal tracts of many animals. However, ruminants emit a much higher volume of CH_4 than nonruminant animals because of the fermentative capacity of the rumen. In the rumen, CH_4 formation is a mechanism for disposing of excess hydrogen from the anaerobic fermentation of dietary carbohydrate. Control of hydrogen ions through methanogenesis helps maintain efficient microbial fermentation by reducing the partial pressure of hydrogen to levels that allow normal functioning of microbial energy transfer enzymes (Morgavi et al., 2010).

The only GHG of concern resulting from enteric fermentation is CH_4. Respiration chambers with N_2O analyzers indicate that enteric fermentation does not result in the production of N_2O (Reynolds et al., 2010). When cattle diets contain moderately high concentrations of nitrates, small amounts of enteric N_2O may be produced (Parker et al., 2018). However, enteric N_2O makes up less than 0.2 percent of enteric emissions, in terms of CO_2 equivalents (Cole et al., 2020a). CH_4 can also arise from hindgut fermentation, but the levels associated with hindgut fermentation (~6–14 percent of daily CH_4 production), are much lower than those of foregut fermentation (Johnson and Johnson, 1995; Immig, 1996).

Enteric CH_4 emissions are a significant contributor to many countries' GHG emissions, and decades of research have gone into characterizing, understanding, modeling, and attempting to mitigate enteric CH_4 emissions. Enteric CH_4 emissions vary with the amount of feed intake as well as diet and stage of production in both beef and dairy cattle, with lactating cows having the highest emission rates. For more information about enteric CH_4 emissions, see appendix 4-A.

4.1.2.2 Housing Emissions

Housing can be a source of GHG and NH_3 when manure accumulates or is stored in housing systems, or when nitrogen accumulates in soils when animals are housed in earthen lots, commonly referred to as dry lots. Differences in populations, regional practices, and climate mean there is a wide variety of animal housing systems—which can lead to differences in both GHG and NH_3 emissions. Housing emissions can also have daily and seasonal trends. Table 4-1 provides an overview of the housing systems considered in this chapter. Emissions of CH_4 from manure deposited on pasture/range are included in the housing section, while N_2O emissions from manure deposited on grazing lands are addressed in chapter 3.

Table 4-1. Overview of Methods Included for GHG Emissions From Animal Housing Systems

Animal Housing Systems		Estimation Method		Description
		CH_4	N_2O	
Dairy	Barn floors	✓		Manure in freestall barns accumulates on the barn floor.
	Dry lot	✓	✓	A paved or unpaved open confinement area without any significant vegetative cover and manure accumulates.
	Deep bedded pack	✓	✓	Bedding material such as straw is added frequently in layers. These become compacted with manure and straw, leading to anaerobic fermentation.
	Liquid/slurry and pit storage below animal confinement	✓	✓	Slatted floors allow manure to accumulate in a pit below the animal confinement.
	Compost barn	✓	✓	Bedding material such as sawdust and manure is composted using an aerobic process, leading to aerobic decomposition of the manure deposited in the housing.
	Pasture/range	✓		Manure is deposited directly to grazing lands.
Beef	Dry lot	✓	✓	A paved or unpaved open confinement area without any significant vegetative cover and manure accumulates.
	Deep bedded pack	✓	✓	Bedding material such as straw is added frequently in layers. These become compacted with manure and straw, leading to anaerobic fermentation.
	Compost barn	✓	✓	Bedding material such as sawdust and manure is composted using an aerobic process, leading to aerobic decomposition of the manure deposited in the housing.
	Pasture/range	✓		Manure is deposited directly to grazing lands.
Swine	Deep bedding	✓	✓	Straw-bedded hoop houses allow manure to accumulate in the straw bedding. As the straw and manure accumulate, the pack begins to compost.
	Liquid/slurry and pit storage below animal confinement	✓	✓	Slatted floors allow manure to accumulate in a pit below the animal confinement.
	Pasture	✓		Manure is deposited directly to pasture.
Poultry	Housing litter	✓	✓	Bedding material such as wood shavings, sawdust, and straw absorb poultry manure.
	Pit storage below animal confinement	✓	✓	Birds are kept in wire cages. Manure collects below the cages in a pit before being applied or moved to storage.

4.1.2.3 Manure Management Emissions

Manure is managed in a wide variety of systems. The resulting GHG emissions differ by GHG and magnitude of emissions per quantity of manure. Table 4-2 provides an overview of the liquid and solid manure systems considered in this report and the resulting GHGs.

Table 4-2. Methods Included for GHG Emissions From Manure Management Systems

Storage and Treatment Practices		Estimation Method CH_4	Estimation Method N_2O	Description
Solid Manure	Solid manure storage (stacked)	✓	✓	Manure is stored in stockpiles that are not disturbed prior to land application.
Solid Manure	Composting	✓	✓	Composting involves the controlled aerobic decomposition of organic material and can occur in different forms. Estimation methods are provided for in-vessel, static pile, intensive windrow, and passive windrow composting.
Liquid Manure	Aerobic lagoon	✓	✓	In aerobic lagoons, manure undergoes biological oxidation as a liquid with natural or forced aeration.
Liquid Manure	Anaerobic lagoon/ runoff holding ponds/storage tanks	✓	✓	Anaerobic lagoons are earthen basins that store animal manure and provide an environment for anaerobic digestion. Lagoons may be covered or uncovered and have a crust or no-crust formation. Multistage lagoons as well as earthen settling basins/weeping walls in combination with lagoons are treated as one lagoon system. Runoff and holding ponds are constructed to capture and store runoff from feedlots and dry lots. In some cases, wash water from dairy parlors may be stored in holding ponds. Storage tanks typically store slurry or wastewater that was scraped or pumped from housing systems. Includes adjustments to estimates due to the use of solid-liquid separation (via mechanical separation like screens or pressing).
Liquid Manure	Anaerobic digester	✓		Anaerobic digesters are manure treatment systems designed to maximize conversion of organic wastes into biogas. These can range from covered anaerobic lagoons to highly engineered systems. CH_4 gas leakage is the main source of GHG emissions; NH_3 and N_2O leakage is negligible.

4.1.3 Management Interactions

The influence of animal production system management practices on GHG emissions is not typically the simple sum of each practice's effect. The influence of one practice can depend on another practice. For example, a change in animal diets can impact both the enteric fermentation and manure management emissions. Because of these interactions, estimating GHG emissions will depend on a complete and accurate description of the management practices used in the operation. As a cross-sectoral example, the available nitrogen after manure storage and treatment impacts emissions expected from land applying manure on croplands. See section 4.5 for more on this interaction.

4.1.4 Mitigation

Changes in animal production system management practices can influence CH_4 and N_2O emissions.

- **Enteric fermentation:** CH_4 emissions can be reduced through diet manipulations, or the use of feed additives or drugs added to feed.[2] Examples of diet manipulations are the

[2] USDA here follows the Food and Drug Administration (FDA) definition of "drug" which includes substances "intended for use in the diagnosis, cure, mitigation, treatment, or prevention of disease." (FDA, 2023).

inclusion of supplemental fat or a different grain type. Diet manipulations may increase or decrease expected emissions. Feed additives or drugs may include 3-nitrooxypropanol (3-NOP), nitrates, or lipid supplementation.

- **Housing:** CH_4 emissions can be reduced by decreasing the time manure is stored in the housing area, particularly during warmer periods of the year. Reducing nitrogen inputs into housing (i.e., via changes in feeding) will reduce N_2O emissions. Some housing strategies emit less N_2O than others, but the choice of strategy may be limited by on-farm factors.
- **Manure management:** In general, decreasing the amount of time manure is stored will decrease both CH_4 and N_2O emissions as there is less time for emissions to occur in this phase of production. Changing from a liquid manure management system to a dry manure management system will reduce CH_4 emissions. CH_4 can also be reduced by covering liquid systems and capturing methane (e.g., a covered lagoon or anaerobic digester). N_2O emissions can be mitigated by covering manure and in some cases adding storage additives/bulking agents.

Emissions from manure can also be affected by dietary factors that affect the quantity and composition of volatile solids (VS) and nitrogen excreted. For example, steam flaking of grains in feedlots increases digestibility and thus decreases the quantity of VS and nitrogen excreted and alters the composition of the VS (less starch vs. more undigestible fiber). By reducing the starch content of the manure there is less available carbon for conversion to CH_4 during storage. These changes potentially decrease manure CH_4 and N_2O emissions compared to dry-rolled corn-based diets (Cole et al., 2020b).

Recognizing the complexities associated with management, the net impact of management changes on emissions can be estimated and the amount of mitigation quantified using the methods described in section 4.2 through section 4.4.

4.1.5 System Boundaries and Temporal Scale

System boundaries are defined by the coverage, extent, and resolution of the estimation methods. The methods in this chapter can be used to estimate GHG emission sources within the production area of an animal production system, including the animals; animal housing; and manure handling, treatment, and storage.

- This chapter considers CH_4 emissions from enteric fermentation, as well as the CH_4 and N_2O emissions from manure management systems or manure stored in housing, as well as indirect N_2O from N losses (NH_3 volatilization and N leaching) from housing and manure management systems that are deposited on the landscape or transported to surface waters.
- Emissions from vehicle transport are not included in the scope of this chapter. These emissions are affected by many variables—age of vehicle, type, fuel efficiency, idle time—that are not direct agricultural emissions; they could instead be considered part of the transport sector (off-road).
- This chapter does not encompass a full life cycle analysis (LCA) of GHG emissions from animal production systems. See chapter 2 for more information on what is and is not included in the scope of the report.
- Emissions that result from grazing (N_2O only) and manure land application are addressed in chapter 3.

The methods in this chapter have a resolution of individual herds within an entity's operation. A herd is defined as a group of animals that are the same species, are housed similarly or graze on the same parcel of land (same diet composition) and use the same manure management system. Emissions are estimated for each individual herd within an operation, then summed to estimate the total animal production emissions for an entity. Animal production totals are then combined with emissions from croplands, grazing lands, and forestry to determine the overall emissions from the operation based on the methods provided in this document. Emissions are estimated on an annual basis. See chapter 2 as needed for additional details on accounting boundaries.

4.1.6 Summary of Selected Methods/Models Sources of Data

The Intergovernmental Panel on Climate Change (IPCC, 2006, 2019) has developed a system of methodological tiers related to the complexity of different approaches for estimating GHG emissions. The methods provided in this chapter range from simple Tier 1 approaches to more complex Tier 2 and 3 approaches. Higher-tier methods are expected to reduce uncertainties in the emission estimates if sufficient activity data and testing are available. See chapter 1 for more information on IPCC tiers.

Table 4-3 summarizes proposed methods and models for estimating GHG emissions from animal production systems. Appendix 4-B summarizes the rationale for the chosen methods. Box 4-1 contains important notes on how to consider all elements within this chapter.

Box 4-1. Important Considerations for Calculating Total Animal Production Systems Emissions

Total emissions estimates for an entity may differ depending on the animal types and management practices employed.

- Consider the units for final estimates. For example, if the calculated emissions units are by head (e.g., kg CH_4/head/day) then multiply by the total number of head, 365 days/year, and the GWP of CH_4 to obtain results in kg CO_2-eq..
- Emissions from each animal type, feed regime, housing, manure storage, and treatment should be converted to CO_2-eq and summed to determine the total entity emissions.
- Ammonia emissions, although not a GHG, as well as N losses via leaching contribute to indirect N_2O emissions and must be estimated. See appendix 4-C.3 for a discussion on the inclusion of these estimates.
- As stated in section 4.1.3, management practices have implications for emissions from different sources which includes implications for other chapters within this guidance. Land application of manure requires inputs noted in section 4.5.

Table 4-3. Overview of Sources and Selected GHG Estimation Methods for Animal Production Systems

Section	Source	Gas	Method
Enteric Fermentation			
4.2.1.1	Dairy cattle	CH_4	Niu et al. (2018) and Moraes et al. (2014) equations
4.2.2.1	Beef cattle	CH_4	Modified IPCC Tier 2 for all beef cattle classes. IPCC Tier 2 for grazing cattle if more specific values are wanted for cow-calf, bulls, and stockers
4.2.3.1	Sheep	CH_4	Howden et al. (1994) equation used when intake data are known and IPCC Tier 2 (2019) when intake data are unknown

Section	Source	Gas	Method
4.2.4.1	Swine	CH_4	IPCC (2006) Tier 1
4.2.5.1	Goats, American bison, llamas, alpacas, and deer	CH_4	IPCC (2019) Tier 1
Housing Emissions			
4.3.2.1	Dairy production systems	CH_4	IPCC (2019) Tier 2 for housing; Chianese et al. (2009) for barn floors
		N_2O	IPCC (2019) Tier 2 using nitrogen excretion (N_{ex}) from Bougouin et al. (2022), Johnson et al. (2016), and Reed et al. (2015)
4.3.3.1	Beef production systems	CH_4	IPCC (2019) Tier 2
		N_2O	IPCC (2019) Tier 2 using N_{ex} from Johnson et al. (2016) and Dong et al. (2014)
4.3.4.1	Swine production systems	CH_4 N_2O	IPCC (2019) Tier 2
4.3.5.1	Poultry production systems	CH_4 N_2O	IPCC (2019) Tier 2
4.3.6.1	Other animals	CH_4, N_2O	Includes sheep, goats, American bison, deer, horses, mules and asses, rabbits, and fur bearing animals using IPCC Tier 1 and 2 (2019)
Manure Storage and Treatment			
4.4.1.1	Solid manure storage (stacked)	CH_4 N_2O	IPCC (2019) Tier 2
4.4.2.1	Composting	CH_4	IPCC (2019) Tier 2 with monthly data
		N_2O	IPCC (2019) Tier 2
4.4.3.1	Aerobic lagoon	CH_4	Methane conversion factor (MCF) for aerobic treatment is negligible and was designated as 0% in accordance with IPCC Tier 1 (2019)
		N_2O	IPCC Tier 2 using IPCC (2019) EFs
4.4.4.1	Anaerobic lagoon, runoff holding pond, storage tanks	CH_4	IPCC (2019) Tier 2 using spreadsheet for determination of MCF developed by IPCC. Also provides guidance on including solid-liquid separation.
		N_2O	Function of the exposed surface area and U.S.-based emission factors
4.4.5.1	Anaerobic digesters	CH_4	IPCC Tier 2 using Clean Development Mechanism EFs for digester types to estimate CH_4 leakage from digesters

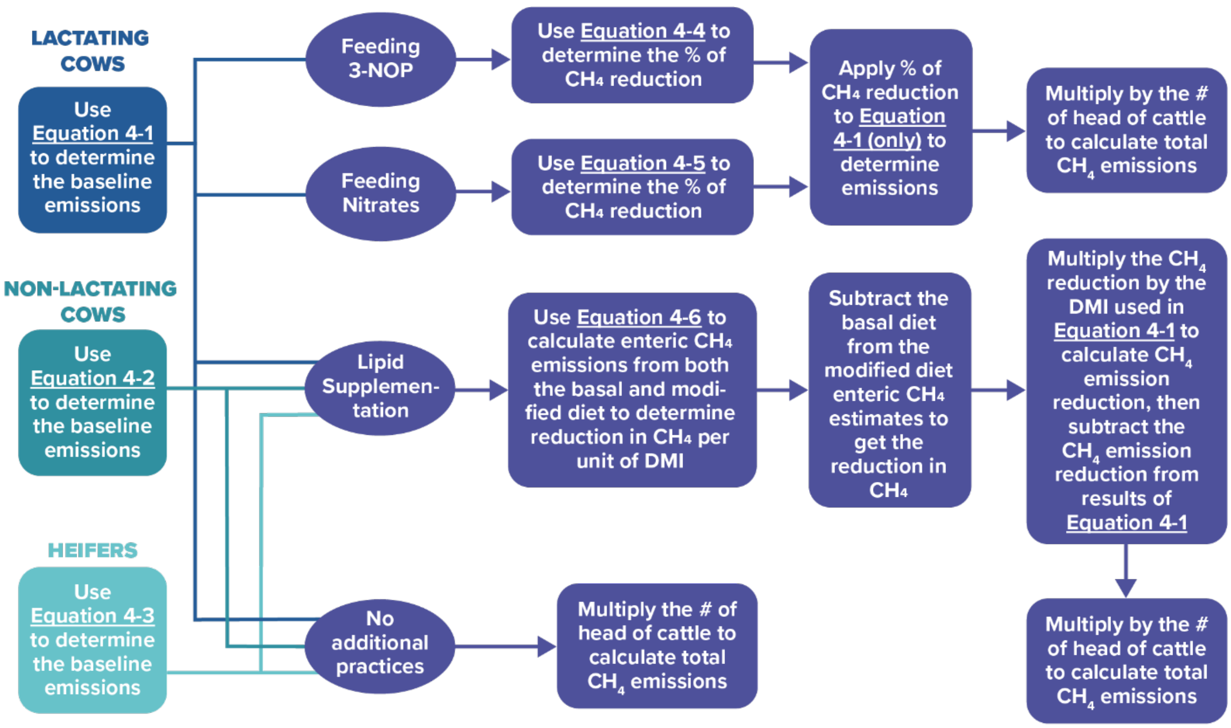
4.2 Enteric Fermentation Estimation Methods

This section provides the recommended method for estimating CH_4 from enteric fermentation. Quantitative methods are provided for dairy, beef, sheep, swine, and other animals (i.e., goats, American bison, llamas, alpacas, and deer). Review considerations for total animal production emissions in box 4-1.

4.2.1 Enteric CH_4 From Dairy Cows

Method for Estimating CH_4 Emissions From Enteric Fermentation in Dairy Cows

- Use Niu et al. (2018) equations for lactating populations and Moraes et al. (2014) for nonlactating adult and heifer populations. Data sources are user input on milk fat, body weight, and dietary intake, as well as dietary composition that, when unavailable, can be calculated from the feedstuffs composition table in appendix 4-E.
- Use equations from Kebreab et al., 2023; Feng et al., 2020; Benaouda et al., n.d. to reflect use of select drugs or diet manipulation practices.



Note: Feeding nitrates is not recommended, and 3-NOP is currently not used within the United States but is under review by the FDA; see box 4-2.

Figure 4-3. Roadmap for Dairy Cattle Emissions Calculations

4.2.1.1 Description of Method

Equation 4-1 presents the recommended method to estimate enteric CH_4 produced by lactating dairy cows. This equation is based on Niu et al. (2018) and was selected because it performed best for North America as compared to other evaluated equations. The recommended methods to estimate enteric CH_4 emissions from dry cows and heifers are based on Moraes et al., 2014 (equation 4-2 and equation 4-3). Review considerations for total animal production emissions in box 4-1.

Equation 4-1: Estimating Enteric Fermentation CH_4 Emissions From Lactating Cows

$$CH_4 = -126 + 11.3 \times DMI + 2.30 \times NDF + 28.8 \times MF + 0.148 \times BW$$

Where:

CH_4	=	enteric methane emissions (g CH_4/head/day)
DMI	=	dry matter intake (kg/head/day)
NDF	=	dietary neutral detergent fiber concentration (% of DM)
MF	=	milk fat concentration (%)
BW	=	body weight (kg)

Equation 4-2: Estimating Enteric CH_4 Emissions From Dry Cows

$$CH_4 = \frac{CH_{4,MJ}}{0.0554}$$

Where:

CH_4	=	enteric methane emissions (g CH_4/head/day)
$CH_{4,MJ}$	=	enteric methane emissions per day (MJ/head/day)
0.0554	=	conversion of MJ CH_4 to g CH_4

and

$$CH_{4,MJ} = 2.381 + 0.053 \times GEI$$

Where:

$CH_{4,MJ}$	=	enteric methane emissions (MJ/head/day)
GEI	=	gross energy intake (MJ/head/day)

and

$$GEI = DMI \times [CP \times 0.056 + Fat \times 0.094 + (100 - CP - Fat - Ash) \times 0.042] \times 4.184$$

Where:

DMI	=	dry matter intake (kg/head/day)
CP	=	dietary crude protein concentration (% of DM)
Fat	=	dietary fat concentration measured as ether extract (% of DM)
Ash	=	dietary ash concentration (% of DM)
4.184	=	conversion from megacalories to megajoules

Equation 4-3: Estimating Enteric CH_4 Emissions From Dairy Heifers

$$CH_4 = \frac{CH_{4,MJ}}{0.0554}$$

Where:

CH_4 = enteric methane emissions (g CH_4/head/day)
$CH_{4,MJ}$ = enteric methane emissions per day (MJ/head/day)
0.0554 = conversion of MJ CH_4 to g CH_4

and

$$CH_{4,MJ} = 1.289 + 0.051 \times GEI$$

Where:

$CH_{4,MJ}$ = enteric methane emissions per day (MJ/head/day)
GEI = gross energy intake (MJ/head/day)

and

$$GEI = DMI \times [CP \times 0.056 + Fat \times 0.094 + (100 - CP - Fat - Ash) \times 0.042] \times 4.184$$

Where:

DMI = dry matter intake (kg/head/day)
CP = dietary crude protein concentration (% of DM)
Fat = dietary fat concentration measured as ether extract (% of DM)
Ash = dietary ash concentration (% of DM)
4.184 = conversion from megacalories to megajoules

Dietary Management Practices

The reductions in enteric CH_4 emissions resulting from drugs or feed additives (e.g., 3-NOP or nitrate) or dietary manipulation (e.g., inclusion of oils and oilseeds) require estimation through application of reduction coefficients or dose-response equations. Recommended management practices for reducing enteric CH_4 production (g/head/day) from lactating dairy cows include feeding 3-NOP, nitrate, and lipid supplementation or inclusion of oilseeds (Arndt et al., 2020). See appendix 4-A.7.4 for more information on these practices.

Box 4-2. Important Caveats

Feed additive impacts to emissions should not be summed as there are not sufficient data to conclude if combined practices would be effective.

Feed additive impacts to emissions past the duration of the literature/studies cited (60–180 days) is unknown; therefore, emission reductions should not be considered in perpetuity.

While studies exist showing the potential to reduce emissions, it is important to note that the drugs mentioned do not claim, nor may they claim, emissions reductions.

Use of nitrates can contribute to higher probability of animal fatalities and should only be done under the supervision of a trained and certified nutritionist.

Use of 3-NOP is currently prohibited in the United States, but under review as an animal drug by the FDA.

See appendix 4-C for research gaps.

Use equation 4-4, equation 4-5, and equation 4-6 to estimate the effect of dietary management practices on enteric CH_4 emissions (Kebreab et al., 2023; Feng et al., 2020; Benaouda et al., n.d.). Note that equation 4-4 and equation 4-5 estimate the CH_4 reduction as a percentage; equation 4-6 estimates the CH_4 emissions from the practice and is for diets containing ether extract from 2.5 to 11 percent on a DM basis. Physical bounds of reasonable maximum reductions are presented within each equation, based on the authors' expert opinion.

Equation 4-4: Estimating Effect of 3-NOP on Enteric CH_4 of Lactating Dairy Cattle

$$CH_4\ reduction = -32.4 - 0.282 \times (3\text{-}NOP - 70.5) + 0.915 \times (NDF - 32.9) + 3.080 \times (Fat - 4.2)$$

Where:

CH_4 reduction	=	enteric CH_4 reduction per day (%) *(a 40% reduction at most is feasible)*
3-NOP	=	3-nitroxypropanol dose (mg/kg of DM)
NDF	=	dietary neutral detergent fiber concentration (% of DM)
Fat	=	dietary crude fat (% of DM)

Equation 4-5: Estimating Effect of Nitrate on Enteric CH_4 of Lactating Dairy Cattle

$$CH_4\ reduction = -20.4 - 0.911 \times (Nitrate - 16.7) + 0.691 \times (DMI - 11.1)$$

Where:

CH_4 reduction	=	enteric methane reduction per day (%) (*a 28% reduction at most is feasible*)
Nitrate	=	nitrate dose (g/kg of DM)
DMI	=	dry matter intake (kg/head/day)
16.7	=	mean nitrate dose (g/kg of DM)
11.1	=	mean dry matter intake (kg/day)

Equation 4-6: Estimating CH_4 Enteric Emissions From Lipid Supplementation in Dairy Cows

$$CH_4\ yield = 25.0 - 0.08 \times EE$$

Where:

CH_4	=	enteric methane yield (g CH_4/kg DMI)
EE	=	dietary ether extract concentration (g/kg of DMI)

This equation is applicable for diets containing ether extract from 25 to 114 g/kg DMI. See box 4-3 for an example of how methane emissions are calculated.

Box 4-3. Example of Lipid Supplementation

Emissions reductions from lipid supplementation are estimated using equation 4-6. Both the basal diet lipid concentration and the supplementation concentration are needed for the equation.

The example below is based on a baseline enteric methane yield of 401 g/head/d (equation 4-1, DMI = 22.8 kg/head/d).

An operator supplementing 20 g lipid/kg DMI on top of a basal diet with 25 g lipid/kg DMI has a total of 45 g lipid/kg DMI.

Methane yield from the modified diet:

$$CH_4\ yield = 25.0 - 0.08\ \times 45 = 21.4\ g\ CH_4/kg\ DMI$$

Methane yield from the basal diet:

$$CH_4\ yield = 25.0 - 0.08\ \times 25 = 23.0\ g\ CH_4/kg\ DMI$$

Subtract the modified diet from the basal diet to determine reduced CH_4 yield:

$$Reduced\ CH_4\ yield = 23.0 - 21.4 =\ 1.6\ g\ CH_4/kg\ DMI$$

Multiply the reduced CH_4 yield by the DMI to determine the total methane reduction (g CH_4/day):

$$CH_4\ yield\ reduction = 1.6\ g\ CH_4/kg\ DMI\ \times 22.8\ kg/DMI/head/day\ = 36.5\ g/head/day$$

Subtract the CH_4 reduction from the methane emissions in equation 4-1:

$$CH_4\ emissions = 401\ g/head/day\ - 36.5\ g/head/day\ = 364.5\ g/head/day$$

4.2.1.2 Activity Data

Type of cattle (lactating dairy cow, nonlactating dairy cow, and dairy heifer), daily dry matter intake (DMI), dietary fat, and lipid supplementation dosage (where applicable) are needed to estimate enteric CH_4 emissions for all dairy cattle categories. Body weight (BW), milk fat concentration (MF), dietary neutral detergent fiber content (NDF), and 3-NOP or nitrate dosage (where applicable) are needed to calculate enteric CH_4 emissions for lactating dairy cows. Estimating enteric CH_4 emissions for nonlactating dairy cows and heifers also requires an estimate of daily gross energy intake (GEI) to be computed from dietary ancillary data. Population is needed if herd or animal group estimates are to be computed from the individual animal results obtained with the recommended equations.

4.2.1.3 Ancillary Data

Dietary concentrations of crude protein (CP) and ash are required to estimate GEI for enteric CH_4 emissions from nonlactating dairy cows and heifers.

4.2.1.4 Limitations and Uncertainty

See appendix 4-B.1 for a discussion of current available information on uncertainties for dairy cattle and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

As noted in box 4-2 there are several limitations for the drugs and feed additives equations presented. See appendix 4-C for additional information on current research gaps. While nitrates have been studied for emissions reduction it is important to note the potential for overdoses which are fatal to cattle. Similarly, while 3-NOP has been studied, its use is prohibited within the United

States (as of December 2022). In addition, there are limits to the application and subsequent calculation of emissions from multiple feed additives, and practices used over several months.

4.2.2 Enteric CH_4 From Beef Cattle

Method for Estimating CH_4 Emissions From Enteric Fermentation in Beef Cattle

- Use the IPCC Tier 2 approach (IPCC, 2019) for all beef cattle classes, with some adjustment factors based on GEI, diet nutrient composition, and grain processing in feedlot cattle.
- Use the IPCC Tier 2 approach (IPCC, 2019) for grazing cattle if more specific values are wanted for cow-calf, bulls, and stockers on pasture/range.
- Data sources are user inputs on dietary feed intake, grain processing, and the feedstuffs composition table in appendix 4-E. Although the equations used are based on existing inventory methods, the method for feedlot cattle considers a large database of feed types (found in appendix 4-E).
- Use of drugs or feed additives can be addressed by applying calculation factors shown in table 4-6.

4.2.2.1 Description of Method

The recommended method to estimate enteric fermentation CH_4 from beef cattle uses the IPCC Tier 2 equation (equation 4-7) to calculate daily emissions as well as an emission factor (DayEmit). The GEI, or daily gross energy intake per animal, must be calculated to determine this emission factor, which can be estimated using the IPCC Tier 2 equation (equation 4-8). Both equations are presented below. The digestible energy should be weighted based on portion of total feed intake from a particular feed type. The digestible energy data for particular feedstuffs can be found in appendix 4-E. The IPCC (2019) equations required to calculate the inputs to equation 4-11 are provided in appendix 4-F. The recommended Y_m (methane conversion factor) for beef replacement heifers, steer stockers, heifer stockers, beef cows, and bulls, which are raised on pasture/rangeland, is 6.5 percent for all regions of the country. Review considerations for total animal production emissions in box 4-1.

Equation 4-7: Modified IPCC Tier 2 Equation for Calculating Enteric CH_4 Emissions for Beef Cattle

$$CH_4 = DayEmit \times Pop_i$$

Where:

CH_4	=	methane emissions (g CH_4/day)
$DayEmit$	=	emission factor (g CH_4/head/day)
Pop_i	=	number of animals with same diet (head)

$$DayEmit = \frac{GEI \times (Y_m \div 100)}{0.056}$$

Where:

$DayEmit$	=	emission factor (g CH_4/head/day)
GEI	=	gross energy intake (MJ/head/day)
Y_m	=	CH_4 conversation factor: fraction of gross energy in feed converted to CH_4 (%)
0.056	=	factor for the energy content of methane (MJ/kg CH_4)

Equation 4-8: IPCC Tier 2 Equation for Calculating Gross Energy Requirements for Beef Cattle

$$GEI = \frac{\left[\left(NE_m + NE_a + NE_l + NE_{work} + NE_p\right) \div REM\right] + \left(NE_g \div REG\right)}{DE \div 100}$$

Where:

GEI	=	gross energy intake (MJ/head/day)
NE_m	=	net energy required by the animal for maintenance (MJ/day), calculated using equation 10.3 in IPCC (2019) based on body weight (*"Weight"*). *See appendix 4-F for IPCC (2019) equations.*
NE_a	=	net energy for animal activity (MJ/day), calculated using equation 10.4 in IPCC (2019) based on NE_m and feeding situation.
NE_l	=	net energy for lactation (MJ/day), calculated using equation 10.8 in IPCC (2019) based on milk production (*"Milk"*) and milk fat (*"Fat"*)
NE_{work}	=	net energy for work (MJ/day), calculated using equation 10.11 in IPCC (2019) based on information on daily hours of work (*"Hours"*)
NE_p	=	net energy required for pregnancy (MJ/day), calculated using equation 10.13 in IPCC (2019) based on NE_m and pregnancy status
REM	=	ratio of net energy available in a diet for maintenance to digestible energy consumed, calculated using equation 10.14 in IPCC (2019) based on DE
NE_g	=	net energy needed for growth (MJ/day), calculated using equation 10.6 in IPCC (2019) based on body weight (*"BW"*), mature weight (*"MW"*), and daily weight gain (*"WG"*)
REG	=	ratio of net energy needed for growth in a diet to digestible energy consumed, calculated using equation 10.15 in IPCC (2019) based on DE
DE	=	digestible energy expressed as a percent of gross energy (%)

Feedlot Cattle

Feedlot cattle have a baseline Y_m of 3 percent; however, this value varies based on the diet the cattle receive. Correction factors to Y_m for feedlot cattle for different scenarios, i.e., diet modifications, are provided in table 4-4 below (see appendix 4-B.2.2 for more details).

Table 4-4. Determination of Adjusted Y_m for Feedlot Cattle

Variable	Reference	Item	Change in Y_m Compared to Baseline Y_m (Base Diet 3%, IPCC 2006, 2019)	Resulting Y_m
Ionophore in diet[a]	Guan et al., 2006; Tedeschi et al., 2003	Ionophore in diet (baseline diet assumes monensin is included at recommended levels)	No change	3%
		Ionophore not in diet	Increase Y_m by 0.30 units[b]	3.3%
Fat content[c]	Beauchemin et al., 2008; Hales and Cole, 2017;	0% supplemental fat	Increase Y_m by 12%[d]	3.36%
		1% supplemental fat	Increase Y_m by 8%	3.24%
		2% supplemental fat	Increase Y_m by 4%	3.12%

Variable	Reference	Item	Change in Y_m Compared to Baseline Y_m (Base Diet 3%, IPCC 2006, 2019)	Resulting Y_m
	Martin et al., 2010; Zinn and Shen, 1996	3% or more added fat (baseline diet assumes 3% supplemental fat and 6% total fat)	No change	3%
Grain type and grain processing	Archibeque et al., 2006; Beauchemin and McGinn, 2005; Hales et al., 2012	Grain in animal diet is steam-flaked or high-moisture corn or sorghum (baseline diet)	No change	3%
		Grain in animal diet is unprocessed or dry-rolled corn or sorghum	Increase Y_m by 20%	3.6%
		Grain in diet is either dry-rolled or steam-flaked barley (baseline diet)	No change	3%
Diet starch: NDF ratio[e]	Beauchemin and McGinn, 2005; Hales et al., 2012, 2013, 2014	Diet has a starch:NDF ratio of 4 (baseline diet is approximately 60% starch and 15% NDF for a starch:NDF ratio of 4)	No change	3%
		Diet starch:NDF ratio is less than 4 (a maximum of 20% forage in the diet DM)	Increase Y_m 0.453 units for each 1 unit less than a diet starch:NDF ratio of 4	Depends on starch:NDF ratio
		Diet starch:NDF ratio is more than 4	Decrease Y_m 0.453 units for each 1 unit greater than a diet starch:NDF ratio of 4	Depends on starch:NDF ratio

The Y_m of 3% for feedlot cattle is adjusted based on deviations from a specified baseline diet. Cattle are assumed to be fed for 90–220 days and diets are balanced for CP, ruminal degradable protein, vitamins, and minerals.

[a] Ionophore compounds are not feed additives, rather drugs that allow the transport of ions across the lipid membrane with cells.

[b] For example, if Y_m = 3% add 0.30 units to get 3.3% of GEI. May also subtract the units to decrease Y_m.

[c] For each percent of added fat (as supplemental fat or in byproducts such as distillers grain that contain about 10 percent fat), decrease by 4% to a maximum of a 12% decrease.

[d] For example, if Y_m = 3% multiply by 1.12 to get 3.36%.

[e] Baseline diet is assumed to contain about 75% grain and has a starch content of about 60%. Diet contains about 8% forage and a total NDF of about 15%.

Cow-Calf, Bulls, and Stockers

If more specific values are wanted for grazing cattle, the most appropriate predictions available for cow-calf, bulls, and stocker entity-scale estimation are IPCC Tier 2 methods for grazing cattle, presented below in equation 4-9. Review considerations in box 4-1.

Equation 4-9: IPCC Tier 2 Equation for Calculating Enteric CH_4 Emissions for Grazing Beef Cattle (if Detailed Feed Information is Unknown)

$$CH_4 = DMI \times \frac{MY}{1{,}000}$$

Where:

CH_4	=	daily methane emissions (kg CH_4/head/day)
DMI	=	dry matter intake (kg/day)
MY	=	methane yield (kg CH_4/kg DMI) (from IPCC table 10.12; see appendix 4-F or table reproduced below)
1,000	=	conversion from g CH_4 to kg CH_4

Livestock Category	Description	Feed quality (%)	MY g CH_4/kg DMI
Nondairy and multi-purpose cattle and buffalo	> 75% forage	DE ≤ 62	23.3
	Rations of > 75% high quality forage and/or mixed rations, forage of between 15 and 75% the total ration mixed with grain, and/or silage	DE 62–71	21.0

Source: IPCC, 2019.

Critical variables to define DMI include measurements or estimations of feed intake and feed quality (chemical composition) for pasture or rangelands. If the intake is unknown, guidelines proposed by Lalman (2004) can be used to determine DMI, as shown in table 4-5 (NASEM, 2016). In this case, the average quality of the grazed forage is estimated to be low, medium, or high.

Table 4-5. Estimated DMI of Beef Cattle Grazing Low-, Medium-, or High-Quality Pastures

Forage Type	Total Digestible Nutrients (%)	Example Forages	Forage DMI as % of BW	
			Dry	Lactating
Low quality	< 52	Dry winter forage, mature legume and grass hay, straw	1.8	2.2
Medium quality	52–59	Dry summer pasture, dry pasture during the fall, late-bloom legume hay, boot stage and early bloom grass hay	2.2	2.5
High quality	> 59	Mid-bloom, early bloom, prebloom legume hay, pre-boot-stage grass hay, lush, growing pasture, silages	2.5	2.7

Source: Lalman, 2004, as cited by NASEM, 2016. DMI is determined based on forage quality and is calculated as a percent of BW. For example, a lactating cow consuming medium quality forage would consume 2.5% of her BW. Assuming a BW of 600 kg, her DMI (used in equation 4-9) is 15 kg/day.

Dietary Management Practices

Potential practices for reducing enteric CH_4 production (g/head/day) from beef cattle in the United States include feeding 3-NOP, nitrate, lipid supplementation, forage supplementation, monensin, and altering the forage to concentrate ratio. Note that there are limitations for some of these practices, as described in box 4-2. Table 4-6 provides information for adjusting enteric CH_4

emissions from beef cattle via these different strategies. If used, multiply the result by emissions determined in equation 4-7 or equation 4-9, for only the number of animals with the same diet.

Importantly, for feedlot cattle combining dietary strategies to reduce enteric CH_4 can have a cumulative effect, but the overall Y_m value should be 2.5–4.5 percent. For grazing cattle, combining dietary strategies to reduce enteric CH_4 can have a cumulative effect, but the overall Y_m value should be 5.5–8 percent (no more or less).

Box 4-4. Example of Applying Dietary Management Practices

Table 4-6 summarizes emissions adjustments from various practices for beef cattle. Use either equation 4-7 or equation 4-9 to estimate baseline emissions and then review the strategies and adjustments in table 4-6 to appropriately adjust. This math will vary slightly depending on if the strategy may increase or decrease the management practice scenario emissions.

For example, if baseline emissions from feedlot finishing cattle are 25 kg CH_4/day and cattle are fed nitrates, <u>subtract</u> the adjustment from 100% of the baseline emissions:

$$CH4_{management\ practice} = 25\ \times \frac{(100\% - 6.5\%)}{100} = 23.4\ kg\frac{CH_4}{day}$$

Whereas, if dietary roughage is increased by 2%, <u>add</u> the adjustment to 100% of the baseline emissions:

$$CH4_{management\ practice} = 25\ \times \frac{(100\% + 2.25\%\ \times 2)}{100} = 26.1\ kg\frac{CH_4}{day}$$

As always, these emissions can be multiplied by 365 days/year to determine annual emissions as well multiplied by GWP to get to CO_2-eq.

Table 4-6. Effects of Management Practices on Beef Cattle Enteric CH_4 Production

Strategy/Technology	Caveats	Enteric Fermentation CH_4 Emission Adjustment	
		Forage Fed[k] Cows and Stocker Cattle	Feedlot Finishing
Lipid (ether extract, EE) supplementation	NA	Emission decreased 4.7 ± 0.9% for each 1% increase in dietary ether extract concentration[a,b] (assuming a baseline diet of 3% EE)	Emission decreased 4.1 ± 0.9% for each 1% increase in dietary EE concentration
3-NOP	Not currently approved for use in the United States	Decrease 17.7 ± 1.93%[c] (inclusion of 100–200 mg NOP/kg DM or 1–2 g/head/day)	Decrease 43.0 ± 22.1%[d] (inclusion of 100–200 mg NOP/kg DM or 1–2 g/head/day)
Nitrates	Recommended with caution (see box 4-2)	Decrease 10.1 ± 1.52%	Decrease 8.95 ± 1.764%[f]
Forage supplementation (hay supplied when pasture/range forage is deficient to meet needs)	NA	Increase in CH_4 g/day 16 ± 5% and decrease of Y_m 14 ± 8%[g]	—

Strategy/Technology	Caveats	Enteric Fermentation CH_4 Emission Adjustment	
		Forage Fed[k] Cows and Stocker Cattle	Feedlot Finishing
Monensin	Following manufacturer label or stated inclusion rates	Decrease 14 ± 6 g CH_4/day or a decrease 8%[h]	Decrease 20 ± 10% for 30 days[i]
Forage to concentrate ratio	NA	—	Emission increased 2.25 ± 0.32% for each 1% increase in dietary roughage[j]

[a] Beauchemin et al., 2007.

[b] Hales and Cole, 2017.

[c] Vyas et al., 2016, 2018; Kim et al., 2019; Martinez-Fernandez et al., 2014; Romero-Perez et al., 2014, 2015.

[d] Vyas et al., 2016, 2018; Alemu et al., 2021; Kim et al., 2019.

[e] Feng et al., 2020; Duthie, 2018; Rebelo et al., 2019; Lee et al., 2015, 2017a; Troy et al., 2015; Hulshof et al., 2012; Alemu et al., 2019; Newbold et al., 2014.

[f] Feng et al., 2020; Lee et al., 2017b; Troy et al., 2015.

[g] Shreck et al., 2017, 2021, Cole et al., 2020a.

[h] Appuhamy et al., 2013; McGinn et al., 2004; Hemphill et al., 2018; Vyas et al., 2018.

[i] Appuhamy et al., 2013; Thornton and Owens, 1981; Guan et al., 2006; Vyas et al., 2018.

[j] Roughage is defined here following the international feed numbering system classification with particle sizes in excess of 1.9 centimeters. Studies used to obtain the 2.25% value used alfalfa hay or grass silage as the forage.

[k] Forage-fed differs from grazing.

4.2.2.2 Activity Data

Type of cattle and stage of production (cow, stocker, feedlot), daily DMI, and/or GEI, as well as type and dosage of drugs or feed additive (where applicable) are required to estimate enteric CH_4 emissions. For estimating emissions from enteric fermentation, the activity data are the same for all animal types.

4.2.2.3 Ancillary Data

Ancillary data include the properties of the diets (e.g., gross energy, digestible energy, starch, fat, NDF) and grain processing methods in the case of feedlot cattle. The feedstuff characteristics needed to calculate CH_4 emissions from beef cattle are included in appendix 4-E (Dairy One, 2021; Ewan, 1989; NASEM, 2016; Preston, 2013).

4.2.2.4 Limitations and Uncertainty

See appendix 4-B.2.2 for additional detail on the analysis and associated uncertainty.

As noted in box 4-2 there are several limitations for the drugs and feed additive equations presented. While nitrates have been studied for emissions reductions it is important to note the potential for overdoses which are fatal to cattle. Similarly, while 3-NOP has been studied, its use is prohibited in the United States (as of December 2022).

4.2.3 Enteric CH_4 From Sheep

Method for Estimating Enteric Fermentation CH_4 Emissions From Sheep

- Use the Howden equation (Howden et al., 1994) if DMI is known.
- Use the IPCC Tier 2 (2019) equation if DMI is unknown.

4.2.3.1 Description of Method

There are two possible methods for estimating enteric CH_4 emissions for sheep. If DMI data are available, use the Howden equation presented in equation 4-10 (Howden et al., 1994). If DMI is unavailable, use the IPCC Tier 2 (2019) equation, equation 4-11, based on new data from pasture-fed sheep. This new equation uses a Y_m value from recent literature of 6.7 percent and assumes the average DMI per day for sheep ranges from 0.6 to 0.8 kg/day. The Y_m value is increased to 7.0 percent if DMI is thought to be less than 0.6 kg/day and is reduced to 6.5 percent if intakes are thought to be greater than 0.8 kg/day (IPCC, 2019). Review considerations for total animal production emissions in box 4-1.

Equation 4-10: Equation for Enteric Fermentation CH_4 Emissions From Sheep

$$CH_4 = DMI \times 0.0188 + 0.00158$$

Where:

CH_4	=	enteric methane emissions (kg CH_4/head/day)
DMI	=	dry matter intake (kg/head/day)

Equation 4-11: IPCC Tier 2 Equation for Enteric Fermentation Emission Factor and Emissions From Sheep If Intake Is Not Known

$$CH_4 = [GEI \times (Y_m \div 100)] \div 55.65$$

Where:

CH_4	=	methane emission (kg CH_4/head/day)
GEI	=	gross energy intake (MJ/head/day) *(calculated using IPCC equation 10.16; see appendix 4-F)*
Y_m	=	methane conversion factor (% of gross energy in feed converted to CH_4)
55.65	=	energy content of CH_4 (MJ/kg)

4.2.3.2 Activity Data

An estimate of DMI or GEI is needed to estimate emissions from enteric CH_4 fermentation.

4.2.3.3 Limitations and Uncertainty

The Howden equation was developed from measurements from sheep grazing tropical forages. This equation has not been verified in animals grazing temperate forages. See appendix 4-B.3 and appendix 4-C.4 for a brief discussion of uncertainty and data gaps for sheep.

4.2.4 Enteric CH_4 From Swine

Method for Estimating Enteric Fermentation CH_4 Emissions From Swine

- Use the IPCC Tier 1 approach, with a U.S. emission factor of 1.5 kg CH_4/head/year (IPCC, 2006).

4.2.4.1 Description of Method

The IPCC (2006) Tier 1 equation for estimating enteric CH_4 from swine multiples the population by an emission factor, as shown in equation 4-12. Review considerations for total animal production emissions in box 4-1.

Equation 4-12: Equation for Enteric Fermentation Emissions From Swine

$$CH_4 = Pop \times \frac{1.5}{365}$$

Where:

CH_4	=	methane emissions (kg CH_4/day)
Pop	=	number of animals (head)
1.5	=	emission factor (kg CH_4/head/year)
365	=	days in year (days/year)

4.2.4.2 Activity Data

Swine population is required for estimating emissions from enteric CH_4 fermentation.

4.2.4.3 Limitations and Uncertainty

See appendix 4-B.4 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.2.5 Enteric CH_4 From Other Animals

Although most enteric fermentation emissions from animals in the United States are from cattle, sheep, and swine, emissions from other animals can also be important to consider, particularly at the entity level. Overall, the animals discussed in this section (goats, American bison, llamas, alpacas, and deer) have much smaller populations than the animals discussed in prior sections. At the entity level, these populations may be significant enough to warrant calculating their emissions, and the availability of research on emissions from these animals allows for at least an introductory level of exploration. Review considerations for total animal production emissions in box 4-1.

4.2.5.1 Description of Method

Goats

Calculate enteric CH_4 emissions from goats as shown in equation 4-13, using the IPCC (2019) Y_m value (5.5 percent) for goats.

Equation 4-13: IPCC Tier 2 Equation for Calculating Enteric Fermentation From Goats

$$CH_4 = [GEI \times (Y_m \div 100) \times 365] \div 55.65$$

Where:

CH_4	=	methane emission (kg CH_4/head/year)
GEI	=	gross energy intake (MJ/head/day) *(calculated using IPCC equation 10.16; see appendix 4-F)*
Y_m	=	methane conversion factor (% of gross energy in feed converted to CH_4)
55.65	=	energy content of CH_4 (MJ/kg)

American Bison, Llamas, Alpacas, and Deer

The U.S. EPA (2020) uses IPCC Tier 1 methodologies to estimate American bison emissions, as currently Tier 1 is the best option to estimate enteric CH_4 emissions from bison.

Use equation 4-14 for estimating enteric CH_4 emissions from American bison, deer, llamas, and alpacas. Table 4-7 provides available emission factors, including a modified factor for American bison as recommended by IPCC (2019) to account for average weight.

Equation 4-14: Tier 1 Equation for Calculating Enteric CH_4 Emissions From Other Animals

$$CH_4 = Pop \times EF_i$$

Where:

CH_4	=	methane emissions per day (kg CH_4/day)
Pop	=	number of animals (head)
EF_i	=	emission factor for other animal (kg CH_4/head/day). See table 4-7.

4.2.5.2 Activity Data

Table 4-7. Enteric CH_4 Emission Factors for American Bison, Llamas, Alpacas, and Deer

Animal	Enteric Fermentation Emission Factor (kg CH_4/Head/Year)[a]
American bison	64[b]
Llamas and alpacas	8
Deer	20

[a] IPCC (2019) Tier 1 estimates.

[b] The IPCC emission factor for buffalo (0.15 kg CH4/head/day or about 55 kg CH4/head/year), adjusted for American bison based on the ratio of live weights of American bison (513 kg) to buffalo (300 kg) to the 0.75 power: $55 \times \left(\frac{513}{300}\right)^{0.75}$

4.2.5.3 Limitations and Uncertainty

See appendix 4-B.5 through appendix 4-B.7 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.3 Housing Estimation Methods

Animal housing emissions include animal manure in housing areas, stored temporarily or for longer periods before moving to an external manure management system. Housing emissions occur from stockpiled or composted manure in lots and barns and from manure solids, slurries, or waters in pits below the housing area or in manure deposited on pasture/range.

Included below are the most up-to-date methods for estimating GHG emissions from barn floors and manure stored in housing areas. Review considerations for total animal production emissions in box 4-1.

Figure 4-4 provides an overview of the emissions calculations for housing and manure management. Equation use is entity-dependent, depending on animal types and management practices, as described in this section and section 4.4.

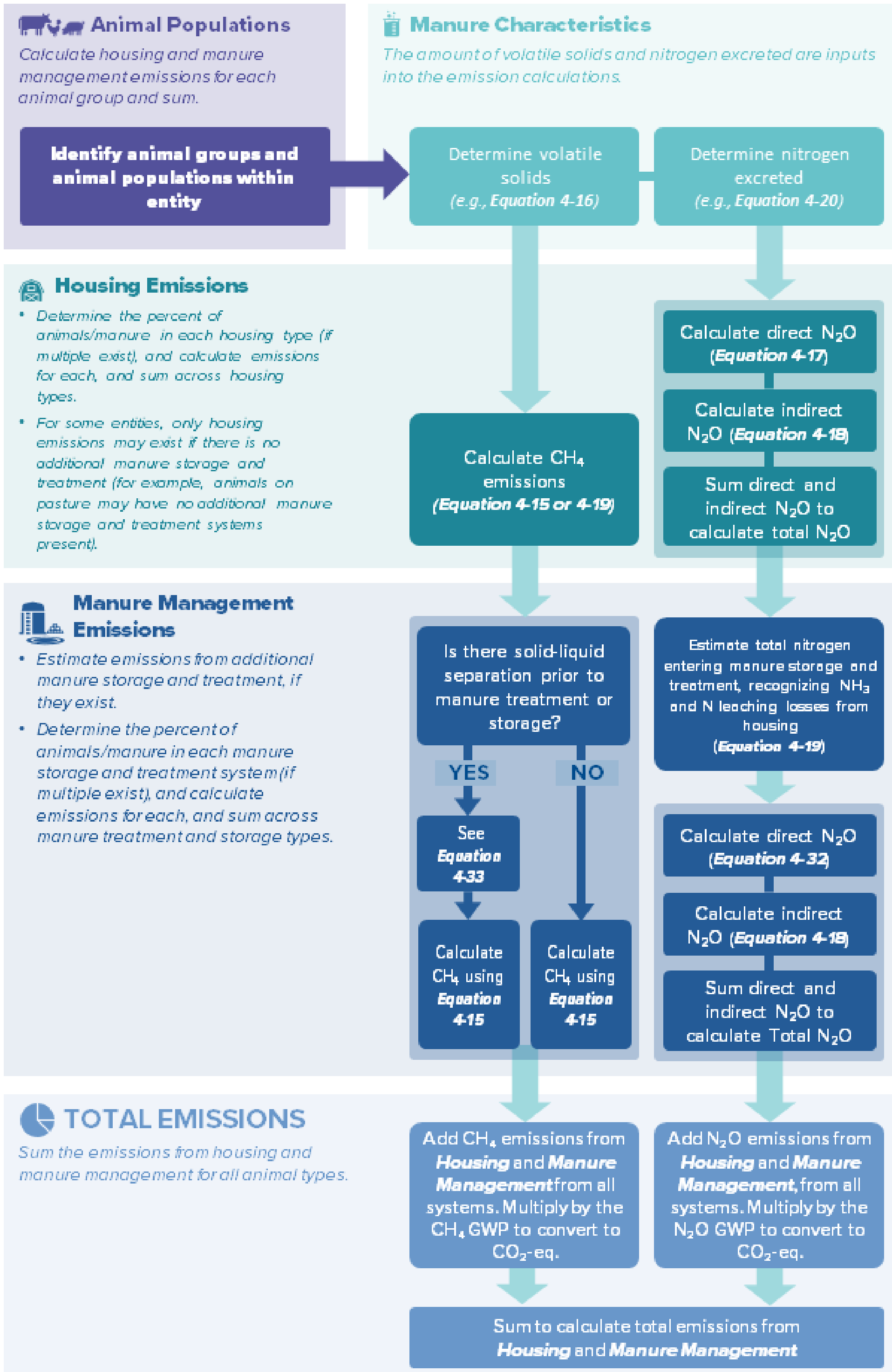


Figure 4-4. Roadmap for Housing and Manure Storage and Treatment Emissions Estimates

Methane

Equation 4-15 and equation 4-16 are common equations in subsequent sections for calculating CH_4 emissions and are presented here to avoid redundancy. These equations are used for each system type. For multiple systems, sum all calculations to determine the total daily emissions. Review considerations for total animal production emissions in box 4-1.

When manure is allowed to accumulate as a stockpile on a dry lot, in a pit below the animal confinement, as a bedded pack, in a composting barn, or on pasture/range, use the IPCC (2019) Tier 2 method to estimate CH_4 emissions, as shown in equation 4-15. This equation uses MCFs and B_0 which are determined based on animal or system type or even average temperature and discussed in subsequent sections. Volatile solids (VS) are also required and calculated in equation 4-16, (IPCC, 2019).

Equation 4-15: IPCC Tier 2 Approach for Estimating CH_4 Emissions From Manure

$$CH_4 = VS \times B_0 \times 0.67 \times \frac{MCF}{100}$$

Where:

CH_4	=	CH_4 emissions (kg CH_4/day)
VS	=	volatile solids (kg/day), use equation 4-16
B_0	=	maximum CH_4 producing capacity for manure (m^3 CH_4/kg VS)
MCF	=	methane conversion factor for the housing or manure management system (%)
0.67	=	conversion factor of m^3 CH_4 to kg CH_4

Equation 4-16: Daily VS Excretion Rates

$$VS = VS_{rate} \times \frac{TAM}{1{,}000} \times Pop \times \frac{\%MMS}{100}$$

Where:

VS	=	volatile solids excretion (kg/day)
VS_{rate}	=	VS excretion rate (kg VS/1,000 kg animal mass/day)
TAM	=	typical animal mass (kg/head)
Pop	=	number of animals (head)
$\%MMS$	=	percent or proportion of manure managed in the housing and/or manure storage, if more than one facility or system. Otherwise, assume 100%.

Nitrous Oxide

Equation 4-17 through equation 4-19 are common equations in subsequent sections calculating N_2O emissions and therefore are presented here to avoid redundancy. Review considerations for total animal production emissions in box 4-1.

Equation 4-17 provides the quantitative method for estimating direct N_2O emissions from animal housing (and manure storage); equation 4-18 from indirect sources. Leaching losses are typical for housing on earthen lots and roofed facilities with bedded packs or composting barns. Where leaching losses are not provided, assume zero percent lost due to leaching. See appendix 4-C.3 for discussion on the uncertainty surrounding the indirect N_2O emissions estimates.

Equation 4-17: IPCC Tier 2 Approach for Estimating Direct N_2O Emissions From Manure

$$N_2O_{direct} = Pop \times N_{ex} \times EF_{N2O} \times \frac{44}{28} \times \frac{\%MMS}{100}$$

Where:

N_2O_{direct}	=	direct nitrous oxide emissions per day (kg N_2O/day)
Pop	=	number of animals (head)
N_{ex}	=	total nitrogen excretion (kg N/head/day)
EF_{N2O}	=	direct N_2O emission factor (kg N_2O-N/kg N)
$\frac{44}{28}$	=	conversion of N_2O-N emissions to N_2O emissions
$\%MMS$	=	percent or proportion of manure managed in the housing and/or manure storage, if more than one facility or system. Otherwise, assume 100%.

Equation 4-18: IPCC Tier 2 Approach for Estimating Indirect N_2O Emissions

$$N_2O_{indirect} = Pop \times N_{ex} \times [\left(\frac{\%NH_3}{100}\right) + \left(\frac{\%Nleach}{100}\right)] \times 0.01 \times \frac{44}{28} \times \frac{\%MMS}{100}$$

Where:

$N_2O_{indirect}$	=	indirect nitrous oxide emissions (kg N_2O/day)
Pop	=	number of animals (head)
N_{ex}	=	total nitrogen excretion (kg N/head/day)
$\%NH_3$	=	percentage of N_{ex} lost as NH_3-N in animal housing
$\%Nleach$	=	percentage of N_{ex} lost as N leaching in animal housing. If no data available, assume 0%.
0.01	=	indirect N_2O emission factor (kg N_2O-N/kg N)
$\frac{44}{28}$	=	conversion of N_2O-N emissions to N_2O emissions
$\%MMS$	=	percent or proportion of manure managed in the housing and/or manure storage, if more than one facility or system. Otherwise, assume 100%.

The remaining nitrogen excreted (N_{ex}) that is not lost as N_2O-N, volatilized as NH_3-N, or lost via leaching from housing, then enters manure storage and treatment. The nitrogen entering storage can be estimated as described in equation 4-19. This remaining total nitrogen value is an input into the N_2O and NH_3 equations for manure stored or treated. See section 4.4.

Equation 4-19: Total Nitrogen Entering Manure Storage and Treatment

$$TN_{storage} = Pop \times N_{ex} \times \left\{1 - \left[\left(\frac{\%NH_3}{100}\right) + \left(\frac{\%Nleach}{100}\right) + EF_{N2O} + \left(EF_{N2O} \times R_{N2(\mathrm{N2O})}\right)\right]\right\}$$

Where:

$TN_{storage}$	=	total nitrogen entering manure storage (kg N/day)
Pop	=	number of animals (head)
N_{ex}	=	total nitrogen excretion (kg N/head/day)
$\%NH_3$	=	percentage of N_{ex} lost as NH_3 in animal housing
$\%Nleach$	=	percentage of N_{ex} lost as N leaching from animal housing. If no data available, assume 0%.
EF_{N2O}	=	direct N_2O emission factor (kg N_2O-N/kg N)
$R_{N2(N2O)}$	=	ratio of N_2:N_2O emissions, the default value is 3 (kg N_2-N/kg N_2O-N)

Uncertainty

For all housing estimation methods, much of the published uncertainty information in inventory guidance—e.g., in IPCC *Good Practice Guidance* (IPCC, 2000) and in the U.S. National GHG Inventory (U.S. EPA, 2020)—focuses on uncertainties present in calculating inventories at the regional or national scale, many of which do not translate to the entity level. Consistent improvement in reporting practices can help remove some of this uncertainty. For this reason, uncertainty estimates are not currently included for these methods. See appendix 4-B.8 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.3.2 CH_4 and N_2O Emissions From Dairy Cow Housing

Method for Estimating Dairy Cows' GHG Emissions From Housing

Methane

- Use the equation developed by Chianese et al. (2009) to calculate CH_4 emissions from barn floors.
- Use the IPCC (2019) Tier 2 approach for CH_4 emissions from manure in housing.

Nitrous Oxide

- Estimate N_{ex} using equations by Bougouin et al. (2022), Johnson et al. (2016), and Reed et al. (2015).
- Use the IPCC (2019) Tier 2 approach for direct N_2O emissions from dairy manure in housing.
- Estimate NH_3-N volatilized and N lost in leaching to determine indirect N_2O emissions.

4.3.2.1 Description of Method

Methane

To estimate CH_4 emissions from barn floors (flushed, scraped, or vacuumed), use the empirical model developed from three freestall barns (Chianese et al., 2009) in equation 4-20.

Equation 4-20: Calculating CH_4 Emissions From Freestall Dairy Barn Floors

$$CH_4 = 0.13 \times T \times \frac{A_{barn}}{1{,}000}$$

Where:

CH_4	=	CH_4 emissions (kg CH_4/day)
T	=	average daily barn temperature (°C) (above 0°C; otherwise, emissions are assumed to be 0 kg CH_4/day)
A_{barn}	=	area of the barn floor covered with manure (m^2)

When manure is allowed to accumulate as a stockpile on a dry lot, in a pit below the animal confinement, as a bedded pack, or in a composting barn, use the IPCC (2019) Tier 2 method to estimate CH_4 emissions (equation 4-15). The data for maximum CH_4 producing capacity (B_0) and MCFs are listed in table 4-8 and table 4-9.

VS excretion is calculated using equation 4-16 (IPCC, 2019), where parameters are based on individual animal category and productivity system. Typical VS excretion in different animal manures is presented in table 4-26.

Nitrous Oxide

The quantitative method for estimating direct N_2O emissions from animal housing is the IPCC Tier 2 approach (equation 4-17). N_2O emission factors for manure stored in housing are listed in table 4-10. Table 4-10 provides estimates of the typical NH_3 loss from different housing facilities and animal species as a fraction of N_{ex}. For manure in deep pits, on dry lots, mixed with bedding, or composted in place, the emission factors are provided in table 4-10. Estimate the amount of N_{ex} by each animal category using equation 4-21 and equation 4-22 (Bougouin et al., 2022; Johnson et al., 2016; Reed et al., 2015). The NH_3-N volatilized or N leached from manure in housing is estimated as a fraction of N_{ex} and is used to calculate the indirect N_2O emissions using equation 4-18.

Equation 4-21: Estimating N_{ex} From Lactating Cows

$$N_{ex} = \frac{\{[DMI \times (CP \div 6.25)] \times 0.66\} + 3.03}{1{,}000}$$

Where:

N_{ex}	=	total nitrogen excretion (kg N/head/day)
DMI	=	dry matter intake (kg/head/day)
CP	=	dietary crude protein concentration (g/kg of DM)
6.25	=	conversion from g of dietary crude protein to g of dietary nitrogen
$\frac{1}{1{,}000}$	=	conversion of grams to kilograms

Equation 4-22: Estimating N_{ex} From Nonlactating Cows and Heifers

$$N_{ex} = \frac{\{[DMI \times (CP \div 6.25)] \times 0.828\} + 15.1}{1{,}000}$$

Where:

N_{ex}	=	total nitrogen excretion (kg N/head/day)
DMI	=	dry matter intake (kg/head/day)
CP	=	dietary crude protein concentration (g/kg of DM)
6.25	=	conversion from g of dietary crude protein to g of dietary nitrogen
$\frac{1}{1{,}000}$	=	conversion of grams to kilograms

The remaining nitrogen excreted (N_{ex}) that is not lost as N_2O-N, volatilized as NH_3-N in housing or leached, enters manure storage and treatment. The nitrogen can be estimated as described in equation 4-19. This remaining total nitrogen value is an input into the N_2O equations for manure stored or treated. See section 4.4.

The NH_3-N and N loss and EF_{N2O} are dependent on the type of housing.

4.3.2.2 Activity Data

Animal population is needed to estimate the daily CH_4 and N_2O emissions, as well as B_0, VS, MCFs, NH_3-N loss, and EF_{N2O} (provided in tables below).

Table 4-8. Maximum CH_4 Producing Capacities and VS Excretion Rates From Dairy Manure

Animal	Maximum CH_4 Producing Capacity (B_0) (m^3 CH_4/kg VS)[a]	VS Rate (kg/1,000 kg Animal Mass/Day)[a]
Dairy replacement heifers	0.17[b]	7.3
Dairy cow	0.24	11 (5.6[c])

[a] Source: USDA Ag Waste Management Field Handbook

[b] Source: U.S. EPA, 2020.

[c] Value in parentheses is for nonlactating mature cow.

Table 4-9. MCFs for Pit Storage Below Animal Confinement, Deep Bedded Systems, Dry Lots, Compost Barns, and Pasture/Range

Housing Type	Storage Time	MCFs (%)					
		Cool Temperate Moist (4.6°C)[a]	Cool Temperate Dry (5.8°C)[a]	Warm Temperate Moist (13.9°C)[a]	Warm Temperate Dry (14.0°C)[a]	Tropical Moist (25.2°C)[a]	Tropical Dry (25.5°C)[a]
Liquid/slurry and pit storage below animal confinement	1 month	6	8	13	15	36	42
	3 months	12	16	24	28	57	62
	4 months	15	19	29	32	64	68
	6 months	21	26	37	41	73	74
	12 months	31	55	64	41	80	80

Housing Type	Storage Time	MCFs (%)					
		Cool Temperate Moist (4.6°C)[a]	Cool Temperate Dry (5.8°C)[a]	Warm Temperate Moist (13.9°C)[a]	Warm Temperate Dry (14.0°C)[a]	Tropical Moist (25.2°C)[a]	Tropical Dry (25.5°C)[a]
Deep bedding	> 1 month	21	26	37	41	73	74
Deep bedding	< 1 month	2.75	2.75	6.5	6.5	18	18
Dry lot	12 months	1	1	1.5	1.5	2	2
Compost barn	12 months	0.50	0.50	1	1	1.5	1.5
Pasture/range	N/A	0.47					

[a] Values represent average annual temperature.

Table 4-10. Typical NH_3-N Losses and Direct N_2O Emission Factors From Dairy Housing Facilities

Facility Description	NH_3 Loss (% of N_{ex})[a]	N Loss Leaching (% of N_{ex})[b]	EF_{N2O} (kg N_2O N/kg N_{ex})[b]
Dry lot including housing, including barn and lot combination	36	3.5	0.02
Barn (natural or mechanical ventilation)	15.5	0	0
Roofed facility—bedded pack (no mix)	25	3.5	0.01
Roofed facility—bedded pack (active mix) including compost barns	50	3.5	0.07
Pasture/range	7	0	See section 4.5 and chapter 3

[a] Sources for dry lot and barn: Bougouin et al. 2016, Hristov et al., 2011, Liu et al., 2017. Source for bedded pack from IPCC, 2019. Sources for pasture: Voglmeier et al., 2018; Sommer et al., 2019; Adhikari et al., 2020; Fischer et al., 2015.

[b] Source: IPCC, 2019.

4.3.2.3 Ancillary Data

Besides the required data noted above, the following entity data are also needed to estimate daily CH_4 and N_2O emissions from dairy cattle housing:

- Animal population
- Animal characteristics (e.g., body weight and stage of production)
- Temperatures (local ambient temperature and manure temperature)
- Dry matter intake and dietary crude protein

4.3.2.4 Limitations and Uncertainty

See appendix 4-B.8.2 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.3.3 CH_4 and N_2O Emissions From Beef Production Housing

Method for Estimating Beef Cattle GHG Emissions From Housing

Methane

- Use the IPCC (2019) Tier 2 method to estimate CH_4 emissions when manure accumulates on feedlot pen surfaces, on pasture/range, or in bedded or compost barns as described below.

Nitrous Oxide

- Estimate N_{ex} for feedlot cattle using the equation of Dong et al. (2014).
- Use the IPCC (2019) Tier 2 approach for direct N_2O emissions from beef cattle manure in housing.
- Estimate NH_3-N volatilized and N lost in leaching to determine indirect N_2O emissions.

4.3.3.1 Description of Method

Methane

When beef manure is allowed to accumulate as a stockpile on a dry lot, in pasture/range, as a bedded pack, or in a composting barn, use the IPCC (2019) Tier 2 method to estimate CH_4 emissions (equation 4-15). The maximum CH_4 producing capacity (B_0) for manure varies by animal category and is provided in table 4-11. The MCFs for manure deposited on a dry lot, pasture/range, from deep bedding, or in compost barns can be found in table 4-12. Calculate VS using equation 4-16 (IPCC, 2019), where parameters are based on individual animal category and productivity system. Typical VS contents in different cattle manures are presented in table 4-26.

Nitrous Oxide

The quantitative method for estimating direct N_2O emissions from animal housing is the IPCC Tier 2 approach (equation 4-17). N_2O emission factors for manure stored in housing are listed in table 4-13. Estimate the quantity of total N_{ex} from feedlot beef cattle using an equation from Dong et al. (2014) (equation 4-23). For a beef feedlot, a default value of 0.069 kg N/kg dry manure can be used if N_{ex} is not calculated. The NH_3-N volatilized, or N leached from manure in housing is estimated as a fraction of N_{ex} and is used to calculate the indirect N_2O emissions using equation 4-18.

The remaining nitrogen excreted that is not lost as N_2O-N, volatilized as NH_3-N or lost via N leaching from housing enters manure storage and treatment, calculated using equation 4-19. Table 4-13 provides estimates on the typical NH_3-N loss from different housing facilities as a fraction of N_{ex}.

Equation 4-23: Estimating N_{ex} of Feedlot Cattle

$$N_{ex} = \frac{(0.51 \times N_{intake} - 14.12) + (0.20 \times N_{intake} + 15.82)}{1{,}000}$$

Where:

N_{ex}	=	total nitrogen excretion (g/head/day)
N_{intake}	=	nitrogen intake per finished animal (g/head/day)
$\frac{1}{1{,}000}$	=	conversion g to kg

$$N_{intake} = DMI \times \frac{\frac{CP}{100}}{6.25}$$

Where:

N_{intake}	=	nitrogen intake per finished animal (g/head/day)
DMI	=	dry matter intake (% body weight)
CP	=	dietary crude protein (% DM)

An alternative approach to calculate NH_3 loss, for use in equation 4-17 or equation 4-19, for feedlot cattle is to use the equation of Todd et al. (2013), which calculates feedlot NH_3 emissions as a function of dietary crude protein and average monthly temperature.

Equation 4-24: Beef Feedlot NH_3 Emissions and N Estimation

$$NH_3 = e^{8.82 - 1627 \times \frac{1}{T} + 0.108 \times CP}$$

Where:

NH_3	=	NH_3 emission from housing (g NH_3/head/day)
T	=	average monthly temperature (K)
CP	=	dietary crude protein (% DM)

For most feedlot situations, the feed intake of a pen of cattle is well documented. When feed intake is unknown, it can be estimated using a variety of equations. Anele et al. (2014) and subsequently NASEM (2016) suggested DMI as a percent of body weight was best estimated from dietary NE_m contents using equation 4-25.

Equation 4-25: Estimating DMI of Feedlot Cattle as a Percent of Body Weight

$$DMI = 1.2425 + 1.9218 \times NE_m - 0.7259 \times NE_m{}^2$$

Where:

DMI	=	dry matter intake (% body weight)
NE_m	=	net energy required by the animal for maintenance, estimated Mcal/kg of the diet (Mcal/kg of DM)

4.3.3.2 Activity Data

Table 4-11. Maximum CH_4 Producing Capacities and VS Excretion Rates From Beef Cattle Manure

Animal	Maximum CH_4 Producing Capacity (B_0) (m^3/kg VS)[a]	VS Rate (kg/1,000 kg Animal Mass/Day)[b]
Beef cows	0.33	7.6
Steers (> 500 lbs)	0.33	7.6
Stockers (all)	0.17	7.6
Cattle on feed	0.33	7.6

[a] Source: U.S. EPA, 2020.

[b] Source: IPCC, 2019.

Table 4-12. MCFs for Deep Bedded Systems, Dry Lots, Compost Barns, and Pasture/Range

Housing Type	Storage Time	MCFs (%)					
		Cool Temperate Moist (4.6°C)[a]	Cool Temperate Dry (5.8°C)[a]	Warm Temperate Moist (13.9°C)[a]	Warm Temperate Dry (14.0°C)[a]	Tropical Moist (25.2°C)[a]	Tropical Dry (25.5°C)[a]
Deep bedding	>1 month	21	26	37	41	73	74
Deep bedding	<1 month	2.75	2.75	6.5	6.5	18	18
Dry lot	12 months	1	1	1.5	1.5	2	2
Compost barn	12 months	0.50	0.50	1	1	1.5	1.5
Pasture/range	N/A	0.47					

[a] Values represent average annual temperature.

Table 4-13. Typical NH_3 Losses and Direct N_2O Emission Factors From Beef Cattle Housing Facilities

Facility Description	NH_3 Loss (% of N_{ex})[a]	N Loss Leaching (% of N_{ex})	EF_{N2O} (kg N_2O N/kg N_{ex})
Feedlot/dry lot	65[a]	3.5	0.02
Roofed facility—bedded pack (no mix)	25	3.5	0.01
Roofed facility—bedded pack (active mix) including compost barns	60	3.5	0.07
Pasture/range	7[b]		See section 4.5 and chapter 3

Source: Unless otherwise specified IPCC, 2019.

[a] Source for feedlot NH_3 losses: Hristov et al., 2011; Liu et al., 2017.

[b] Sources for pasture: Voglmeier et al., 2018; Sommer et al., 2019; Adhikari et al., 2020; Fischer et al., 2015.

4.3.3.3 Ancillary Data

Besides the required data noted above, the following entity data are also needed to estimate daily CH_4 and N_2O emissions from beef cattle housing:

- Animal population
- Animal characteristics (e.g., body weight and stage of production) and dietary information
- Temperatures (local ambient temperature and manure temperature)
- Feed information

4.3.3.4 Limitations and Uncertainty

See appendix 4-B.8.2 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.3.4 CH_4 and N_2O Emissions From Swine Production Housing

Method for Estimating Swine GHG Emissions From Housing

Methane

- Use the IPCC (2019) Tier 2 method to estimate CH_4 emissions when manure is allowed to accumulate below the animal confinement, in bedded barns, or on pasture as described below.

Nitrous Oxide

- Use the IPCC (2019) Tier 2 approach for nitrogen intake, retention, and excretion.
- Use the IPCC (2019) Tier 2 approach for N_2O from manure in housing.

4.3.4.1 Description of Method

Methane

Use the IPCC (2019) Tier 2 method (equation 4-15) to estimate CH_4 emissions from swine housing, regardless of where swine are housed (e.g., pasture, bedded pack in a barn, pit below the animal confinement). The maximum CH_4 producing capacity (B_0) for manure varies by animal category and is provided in table 4-14. The MCFs for manure stored in a deep pit, from bedding, or in pasture can be found in table 4-15. VS are calculated using equation 4-16 (IPCC, 2019), where parameters are based on individual animal category. Typical VS contents in different manures are presented in table 4-26.

Nitrous Oxide

The quantitative method for estimating N_2O emissions from animal housing is the IPCC Tier 2 approach (equation 4-17). N_2O emission factors for manure stored in housing are listed in table 4-17. Estimate the amount of N_{ex} for each swine category based on total nitrogen intake (N_{intake}) and nitrogen retained by animals ($N_{retention}$) (equation 4-26). Equation 4-27 and equation 4-28 provide the methods for estimating the nitrogen intake and retention for the different swine classes as recommended by IPCC.

Equation 4-26: Estimating N_{ex} From Swine

$$N_{ex} = N_{intake} - N_{retention}$$

Where:

N_{ex}	=	total nitrogen excretion (kg/head/day)
N_{intake}	=	nitrogen intake per finished animal (kg/head/day)
$N_{retention}$	=	nitrogen retained per finished animal (kg/head/day)

Equation 4-27: Estimating N_{intake} and $N_{retention}$ From Growing Pigs

$$N_{intake} = DMI \times [(C_{CP} \div 100) \div 6.25]$$

$$N_{retention} = \left[\left(BW_f - BW_i\right) \times N_{gain}\right] \div G$$

Where:

N_{intake}	=	nitrogen intake per finished animal (kg/head/day)
$N_{retention}$	=	nitrogen retained per finished animal (kg/head/day)
N_{gain}	=	fraction of nitrogen retained at a given BW (calculate for the final BW of the phase: for example, for a finishing hog that weighed 109 kg at slaughter, use a value of 0.021 kg N/kg BW gain)
DMI	=	dry matter intake (kg/head/day)
C_{CP}	=	percentage of crude protein in DM (%)
BW_f	=	final body weight at the end of the growth stage (kg)
BW_i	=	initial body weight (kg)
GS	=	number of days in the growth stage (default value is between 154 and 168 days)

Equation 4-28: Estimating N_{intake} and $N_{retention}$ From Breeding Sows

$$N_{intake} = DMI \times [(C_{CP} \div 100) \div 6.25]$$

$$N_{retention} = \frac{\left[\left(0.025 \times FR \times S_{wtgain}\right) + \left(0.025 \times LTSZ \times FR \times \frac{Pig_{weanwt} - Pig_{birthwt}}{0.98}\right)\right]}{FR \times RC}$$

Where:

N_{intake}	=	nitrogen intake per finished animal (kg N/head/day)
$N_{retention}$	=	nitrogen retained per finished animal (kg N/head/day)
DMI	=	dry matter intake (kg N/head/day)
C_{CP}	=	percentage of crude protein in DM (%)
6.25	=	conversion from kg of dietary protein to kg of dietary N
FR	=	fertility rate of sows (parturitions/year)
S_{wtgain}	=	live weight change of sows during gestation (kg)
$LTSZ$	=	litter size (head)
Pig_{weanwt}	=	live weight of piglets at weaning (kg/head)
$Pig_{birthwt}$	=	live weight of piglets at birth (kg/head)
RC	=	days in the reproductive cycle (default value is 146 days)

Some of the nitrogen excreted is volatilized as NH_3, so the estimation of NH_3 losses is necessary to estimate N_2O emissions using a nitrogen balance approach. The NH_3 lost via volatilization and N leached from swine housing is estimated as a fraction of N_{ex} according to table 4-17.

4.3.4.2 Activity Data

Table 4-14. Maximum CH_4 Producing Capacities and VS Rates From Swine Manure

Animal	Maximum CH_4 Producing Capacity (B_0) (m^3/kg VS)	VS Rate (kg/1,000 kg Animal Mass/Day)
Growing swine	0.48	3.9
Breeding swine	0.48	1.8

Source: IPCC, 2019.

Table 4-15. MCFs for Pit Storage Below Animal Confinement, Deep Bedded Systems, and Pasture

Housing Type	Storage Time	MCF (%)					
		Cool Temperate Moist (4.6)[a]	Cool Temperate Dry (5.8)[a]	Warm Temperate Moist (13.9)[a]	Warm Temperate Dry (14.0)[a]	Tropical Moist (25.2)[a]	Tropical Dry (25.5)[a]
Liquid/slurry and pit storage below animal confinement	1 month	6	8	13	15	36	42
	3 months	12	16	24	28	57	62
	4 months	15	19	29	32	64	68
	6 months	21	26	37	41	73	74
	12 months	31	55	64	41	80	80
Deep bedding	> 1 month	21	26	37	41	73	74
Deep bedding	< 1 month	2.75	2.75	6.5	6.5	18	18
Pasture	N/A	0.47					

[a] Values represent average annual temperature (°C).

Table 4-16. Nitrogen Gain by Growth Stage

Facility Description	N_{gain} (kg N/kg BW)
Nursery (4–7 kg)	0.031
Nursery (7–20 kg)	0.028
Grower (20–40 kg)	0.025
Grower (40–80 kg)	0.024
Finisher (80–120 kg)	0.021

Source: IPCC, 2019.

Table 4-17. Typical NH_3 Losses and Direct N_2O Emission Factors From Swine Housing Facilities

Facility Description	NH_3 Loss (% of N_{ex})[a]	N loss Leaching (% of N_{ex})	EF_{N2O} (kg N_2O N/kg N_{ex})[b]
Roofed facility—bedded pack (no mix)	40	3.5	0.01
Roofed facility—bedded pack (active mix) including compost barns	65	3.5	0.07

Facility Description	NH_3 Loss (% of N_{ex})[a]	N loss Leaching (% of N_{ex})	EF_{N2O} (kg N_2O N/kg N_{ex})[b]
Roofed facility—pit storage below animal confinement	25	0	0.002
Pasture	19		See section 4.5 and chapter 3

[a] Source for everything except pasture: IPCC (2019). Source for pasture: Sommer et al., 2019.

[b] Source: IPCC, 2019.

4.3.4.3 Ancillary Data

Besides the required data noted above, the following entity data are also needed to estimate daily CH_4 and N_2O emissions from swine housing:

- Animal population
- Animal characteristics (e.g., body weight and growth stage) and dietary information
- Bedding characteristics
- Temperatures (local ambient temperature and manure temperature)
- Feed information

4.3.4.4 Limitations and Uncertainty

See appendix 4-B.8.2 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.3.5 CH_4 and N_2O Emissions From Poultry Housing

Method for Estimating Emissions From Poultry Housing

Methane

- Use the IPCC (2019) Tier 2 approach with barn capacity and manure CH4 emission factors per poultry type.
- The IPCC emission factor for poultry enteric CH4 production is 0. Emissions from hindgut fermentation are small and generally considered part of housing emissions.

Nitrous Oxide

- Use the IPCC (2019) Tier 2 approach for N_{ex}.
- Use the IPCC (2019) Tier 2 approach for N_2O from manure in housing.

4.3.5.1 Description of Method

Methane

Use the IPCC (2019) Tier 2 method (equation 4-15) to estimate CH_4 emissions from poultry production systems. The maximum CH_4 producing capacity (B_0) is provided in table 4-18. The MCFs for manure deposited in poultry houses can be found in table 4-19.

Calculate VS using equation 4-16 (IPCC, 2019), where parameters are based on individual animal category and productivity system. Typical VS contents in different poultry manures are presented in table 4-26.

Nitrous Oxide

The quantitative method for estimating N_2O emissions from poultry housing is the IPCC Tier 2 approach (equation 4-17). N_2O emission factors and NH_3 lost from manure for meat and egg-producing birds as a fraction of N_{ex} for manure stored in housing are listed in table 4-20.

The remaining nitrogen excreted that is not lost as N_2O or volatilized as NH_3 in housing enters manure storage and treatment. If data are not available to track the nitrogen that is transferred along with the manure-to-manure storage and treatment, the nitrogen can be estimated as described in equation 4-19. This remaining total nitrogen value is an input into the N_2O equations for manure stored or treated.

Estimate the quantity of total N_{ex} using equations from IPCC (IPCC 2019) and ASABE (2005). Equation 4-29 and equation 4-30 are the equations recommended by IPCC (2019) for estimating N_{ex} from poultry produced for meat (broilers, turkeys, ducks) and egg-laying poultry, respectively.

Equation 4-29: Estimating N_{ex} From Poultry Produced for Meat

$$N_{ex} = [DMI \times (CP\% \div 100 \div 6.25)] - \{[(BW_f - BW_i) \times 0.028] \div PP\}$$

Where:

N_{ex}	=	total nitrogen excretion (kg N/head/day)
DMI	=	dry matter intake (kg DMI/head/day)
$CP\%$	=	percentage of crude protein in the diet (%)
BW_f	=	final body weight (kg)
BW_i	=	initial body weight (kg)
PP	=	production period (length of time from chick to slaughter) (days)

Equation 4-30: Estimating N_{ex} From Egg-Laying Poultry

$$N_{ex} = [DMI \times (CP\% \div 100 \div 6.25)] - \{0.028 \times WG + [(0.0185 \times EP) \div 1{,}000]\}$$

Where:

N_{ex}	=	total nitrogen excretion (kg N/head/day)
DMI	=	dry matter intake (kg DMI/head/day)
$CP\%$	=	percentage of crude protein in the diet (%)
WG	=	average daily weight gain for cohort (kg/head/day)
EP	=	egg mass production (g egg/head/day); default egg weight is 60 g for light layer strains and 63 g for heavy layer strains

4.3.5.2 Activity Data

Table 4-18. Maximum CH_4 Producing Capacities and VS Rates From Poultry Manure

Animal	Maximum CH_4 Producing Capacity (B_0) (m^3/kg VS)	VS Rate (kg/1,000 kg Animal Mass/Day)
Poultry—layer	0.39	9.4
Poultry—meat	0.36	16.8

Source: IPCC, 2019.

Table 4-19. MCFs for Poultry Manure With and Without Litter

Housing Type	All Climates (%)
Poultry manure with and without litter	1.5

Table 4-20. Typical NH_3 Losses and Direct N_2O Emission Factors From Poultry Housing Facilities

Facility Description	NH_3 Loss (% of N_{ex})	EF_{N2O} (kg N_2O N/kg N_{ex})
Roofed facility—with litter	40	0.001
Roofed facility—without litter	48	0.001
Use of alum or another acidifying agent in litter	20[a]	—

Source: IPCC, 2019.

[a] Source: Author expert judgment based on Anderson et al. (2020), Eugene et al. (2015), Madrid et al. (2012), and Moore et al. (2008).

4.3.5.3 Ancillary Data

Besides the required data listed in the tables above, the following entity data are also needed to estimate daily CH_4 and N_2O emissions from poultry housing:

- Animal population and animal characteristics (e.g., body weight, growth potential, egg production)
- Feed intake
- Temperatures (local ambient temperature and manure temperature)

4.3.5.4 Limitations and Uncertainty

See appendix 4-B.8.2 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.3.6 CH_4 and N_2O Emissions From Other Animals Housing

Method for Estimating Emissions From Other Animals

Methane

- Use the IPCC (2019) Tier 1 approach, or Tier 2 when data are available.

Nitrous Oxide

- Use the IPCC (2019) Tier 1 approach for N_{ex}.
- Use the IPCC (2019) Tier 2 approach for N_2O from manure in housing.

4.3.6.1 Description of Method

Methane

To estimate CH_4 emissions from other animal housing—sheep, goats, American bison, deer, horses, mules and asses, rabbits, and fur bearing animals—use the IPCC (2019) Tier 2 method (equation 4-15) when activity data are available; otherwise, use the Tier 1 default emission factors provided in table 4-21 and table 4-22, in lieu of using MCF and B_0 values.

Nitrous Oxide

To estimate N_2O emissions from other animals, use the IPCC Tier 2 approach (equation 4-17) when activity data are available; otherwise, use the Tier 1 default values.

4.3.6.2 Activity Data

Table 4-21. Housing (Dry Lot) Methane Emission Factors by Animal Category and Climate Zone

Animal	CH_4 Emission Factor (g CH_4/kg VS)		
	Cool	Temperate	Warm
Sheep	1.3	1.9	2.5
Goats	1.2	1.8	2.4

Source: IPCC, 2019, assuming high-productivity systems.

Table 4-22. CH_4 Emission Factors by Animal Category, MCF for Housing (Pasture/Range), Maximum CH_4 Producing Capacity of Manure, and VS Excretion

Animal	Methane Emission Factor		Maximum CH_4 Producing Capacity (B_0) (m^3/kg VS)	VS	
	MCF % [a]	kg CH_4/Head/Year		kg/Day	kg/1,000 kg Animal Mass/Day
American bison[b]	0.47	—	0.10	—	7.7
Sheep	0.47	—	0.19	—	8.2
Goats	0.47	—	0.18	—	9
Deer	—	0.22	—	—	—
Horses	0.47	—	0.33	—	6.1

Animal	Methane Emission Factor		Maximum CH_4 Producing Capacity (B_0) (m^3/kg VS)	VS	
	MCF % [a]	kg CH_4/Head/Year		kg/Day	kg/1,000 kg Animal Mass/Day
Mules and asses	0.47	—	0.33	—	7.2
Rabbits	—	0.08	0.32	0.10	—
Fur-bearing animals	—	0.68	0.25	0.14	—

[a] Assuming animals on pasture/range (IPCC, 2019)

[b] Surrogating values for buffalo from IPCC (2019).

Table 4-23. N_{ex} Values for Other Animals

Category of Animal	Units	N_{ex}
Sheep	kg N/1,000 kg BW/day	0.35
Goats	kg N/1,000 kg BW/day	0.46
American bison	kg N/1,000 kg BW/day	0.40[a]
Horses	kg N/hd/yr	0.25
Mules and asses	kg N/hd/yr	0.30
Deer	kg N/hd/yr	0.67
Rabbits	kg N/hd/yr	8.10
Mink	kg N/hd/yr	4.59

[a] Average of values for western Europe and eastern Europe.

Table 4-24. Typical NH_3 Losses and Direct N_2O Emission Factors From the Housing of Other Animals

Facility Description	NH_3 Loss (%)	EF_{N2O} (kg N_2O N/kg N_{ex})
Pasture/range/paddock	—	See section 4.5 and chapter 3
Dry lot	30	0.02

Source: IPCC, 2019. IPCC (2019) does not have guidance for rabbit and mink housing.

4.3.6.3 Ancillary Data

Besides the required data listed in the tables above, the following entity data are also needed to estimate daily CH_4 and N_2O emissions from housing other animals:

- Animal population and animal body weight
- Temperatures (local ambient temperature and manure temperature)

4.3.6.4 Limitations and Uncertainty

See appendix 4-B.8.2 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.4 Manure Management Estimation Methods

Manure can be handled as a solid or liquid. It can be applied directly to land, stored, or treated before storage or land application. In some practices, solids are separated from the liquid manure stream and treated using a solid handling system.[3] Individual practices may be combined to treat manure based on the need at the entity level. Each manure management practice is described as an individual unit practice in this document. The references for estimation of GHG emission for individual practices are listed in table 4-3. Review considerations for total animal production emissions in box 4-1.

Note for all manure management estimation methods, much of the published uncertainty information in inventory guidance—e.g., in IPCC *Good Practice Guidance* (IPCC, 2000) and in the U.S. National GHG Inventory (U.S. EPA, 2020)—focuses on uncertainties present in calculating inventories at the regional or national scale, many of which do not translate to the entity level. Consistent improvement in reporting practices can help remove some of this uncertainty. For this reason, uncertainty estimates are not currently included for these methods. See appendix 4-B.8.2 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.4.1 CH_4 and N_2O From Solid Manure Storage (Stockpiles)

Method for Estimating Emissions From Manure Storage and Treatment— Solid Manure Storage (Stockpiles)

Methane

- Use the IPCC Tier 2 approach with IPCC and U.S. EPA Inventory emission factors and VS of animal manure.
- Solid-liquid separation is addressed in section 4.4.4 but should be considered here too if separated solids are stored as stockpiles.

Nitrous Oxide

- Use the IPCC Tier 2 approach with U.S.-based emission factors and total nitrogen.
- The NH_3-N lost from stockpiled manure is used to calculate the indirect N_2O emissions.

4.4.1.1 Description of Method

Methane

Use the IPCC Tier 2 approach to estimate CH_4 emissions and is described in equation 4-15 (IPCC, 2019). The data for maximum CH_4 production capacity (B_0) and MCF are listed in table 4-25, table 4-26, and table 4-27. VS are calculated using equation 4-16 (IPCC, 2019), where parameters are based on individual animal categories and productivity systems. Typical VS excretion in different animal manures is presented in table 4-26. Review box 4-1 for considerations for total animal production emissions.

Nitrous Oxide

The only quantitative method for estimating N_2O emissions from solid manure is the IPCC Tier 2 approach, which is also used for the U.S. Inventory. This approach uses emission factors from IPCC (2019) guidelines, and total nitrogen values are estimated according to equation 4-19. Equation

[3] No method is provided for solid-liquid separation as GHG emissions are negligible. While no method is provided, solids separation impacts the potential emissions from other systems (e.g., anaerobic lagoons) as its use would remove total solids (and therefore VS or total nitrogen) from those systems.

4-31 and equation 4-18 present the equations to estimate the direct and indirect N_2O emissions for solid manure, respectively. N_2O emission factors for solid manure storage are listed in table 4-28.

Equation 4-31: IPCC Tier 2 Approach for Estimating Direct N_2O Emissions

$$E_{N2O} = EF_{N2O} \times TN_{storage} \times \frac{44}{28}$$

Where:

E_{N2O}	=	nitrous oxide emissions (g N_2O/day)
EF_{N2O}	=	direct nitrous oxide emission factor (kg N_2O-N/kg N)
$TN_{storage}$	=	total nitrogen entering manure storage at a given day (kg/day), use equation 4-19
$\frac{44}{28}$	=	conversion of N_2O-N emissions to N_2O emissions

4.4.1.2 Activity Data

Table 4-25. Maximum CH_4 Producing Capacities (B_0) From Different Animal Manures

Animal	Maximum CH_4 Producing Capacity (B_0) (m^3/kg VS)[a]	Animal	Maximum CH_4 Producing Capacity (B_0) (m^3/kg VS)[a]
Beef replacement heifers	0.17[b]	Layer (dry)	0.39
Dairy replacement heifers	0.17[b]	Layer (wet)	0.39
Mature beef cows	0.17[b]	Broiler	0.36
Steers (> 500 lbs)	0.17[b]	Turkey	0.36
Stockers (all)	0.17[b]	Duck	0.36
Cattle on feed	0.33[b]	Sheep	0.19[b]
Dairy cow	0.24[b]	Feedlot sheep	0.36[b]
American bison	0.1[c]	Goat	0.18[b]
Market swine	0.48	Horse	0.3
Breeding swine	0.48	Mule/ass	0.33
Rabbits	0.32	Fur-bearing animals	0.25

[a] Source: IPCC, 2019, unless otherwise noted.

[b] Source: U.S. EPA, 2020.

[c] There are no data for North America; the data from western Europe are used to calculate the estimate. Data for buffalo used as a surrogate for American bison.

Table 4-26. Typical VS Excretion in Different Animal Manures

Animal	VS Rate (kg/1,000 kg Animal Mass/Day)	Animal	VS Rate (kg/1,000 kg Animal Mass/Day)
Beef replacement heifers	7.6	Layer (dry)	14.5
Dairy replacement heifers	9.3	Layer (wet)	14.5
Mature beef cows	7.6	Broiler	16.8

Animal	VS Rate (kg/1,000 kg Animal Mass/Day)
Steers (> 500 lbs)	7.6
Stockers (all)	7.6
Cattle on feed	7.6
Dairy cow	9.3
American bison[a]	7.7[a]
Market swine	3.9
Breeding swine	1.8
Rabbits	0.10[b]

Animal	VS Rate (kg/1,000 kg Animal Mass/Day)
Turkey	10.3
Duck	7.4
Sheep	8.2
Feedlot sheep	8.2
Goat	9
Horse	5.65
Mule/ass	7.2
Fur-bearing animals	0.14[b]

Source: IPCC, 2019.

[a] There are no data for North America; the data from western Europe are used to calculate the estimate.

[b] Units are kg VS/day.

Table 4-27. MCFs for Storage of Solid Manure From Different Animals and Practices

Animal	MCF (%)		
	10 14°C	15 25°C	26 28°C
Dairy cattle	2	4	5
Beef cattle	2	4	5
American bison[a]	2	4	5
Market swine	2	4	5
Breeding swine	2	4	5
Layer (dry)	1.5	1.5	1.5
Broiler	1.5	1.5	1.5
Turkey	1.5	1.5	1.5
Duck	1	1.5	2
Sheep	1	1.5	2
Goat	1	1.5	2
Horse	1	1.5	2
Mule/ass	1	1.5	2
Covered/compacted	2	4	5
Bulking agent addition	0.5	1.0	1.5
Additives	1	2	2.5

Source: IPCC, 2019.

[a] There are no data for North America; the data from western Europe are used to calculate the estimate.

Table 4-28. Direct N_2O Emission Factors for Solid Manure Storage

Type of Storage	Direct N_2O Emission Factor (kg N_2O N/kg N_{ex})
Storage of solid manure	0.01
Solid storage covered/compacted	0.01
Solid storage bulking agent addition	0.005
Solid storage additives	0.005

Sources: IPCC, 2019; U.S. EPA, 2020.

Table 4-29. Nitrogen Loss Fractions for Volatilization and Leaching for Solid Manure Storage

	Swine		Dairy Cow		Poultry		Other Cattle		Other Animals	
	%NH_3 N	%N_{leach}	%NH_3 N	%N_{leach}	%NH_3 N	%N_{leach}	%NH_3 N	%N_{leach}	%NH_3 N	%N_{leach}
Storage of solid manure	45	2	30	2	40	2	45	2	12	2
Solid storage covered/ compacted	22	0	14	0	20	0	22	0	5	0
Solid storage bulking agent addition	58	2	38	2	54	2	58	2	15	2
Solid storage additives	17	2	11	2	16	2	17	2	4	2

Source: IPCC, 2019.

4.4.1.3 Ancillary Data

To estimate the daily emissions from solid manure storage, the following information is needed:

- Animal type
- Animal population
- Temperatures (local ambient temperature and manure temperature)
- Total nitrogen content of the manure

Although daily estimates for the activity data are optimal, tracking this level of detail would be burdensome. Annual estimates do not allow for seasonal variation in diets and climate. Consequently, disaggregation of the data by season or by periods of major shifts in animal population is suggested.

4.4.1.4 Limitations and Uncertainty

See appendix 4-B.8.2 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.4.2 CH_4 and N_2O From Composting

Method for Estimating Emissions From Manure Storage and Treatment—Composting

Methane

- Use the IPCC Tier 2 approach with data on VS of animal manure.
- Solid-liquid separation is addressed in section 4.4.4 but should be considered here too if separated solids are composted.

Nitrous Oxide

- Use the IPCC Tier 2 approach with data on a N_2O emission factor.
- The method depends on whether the system is in a vessel, a static pile, an intensive windrow, or a passive windrow.
- The NH_3-N lost from composting manure is used to calculate the indirect N_2O emissions.

4.4.2.1 Description of Method

The IPCC Tier 2 methodology is provided for estimating CH_4 and N_2O emissions from composting (IPCC, 2019). This methodology uses country-specific emission factors from the U.S. National GHG Inventory (U.S. EPA, 2020). The amount of manure, VS content, and temperature are entity-specific. Review considerations for total animal production emissions in box 4-1.

Methane

Use the IPCC Tier 2 approach to estimate CH_4 emissions, as described in equation 4-15 (IPCC, 2019). The data for B_0 and MCF are listed in table 4-11 and table 4-30. Calculate VS using equation 4-16 (IPCC, 2019), with parameters based on individual animal categories and productivity systems. Table 4-26 lists typical VS excretion in different animal manures.

Nitrous Oxide

Use the IPCC Tier 2 method to estimate direct and indirect N_2O emissions from composting, as shown in equation 4-31 and equation 4-18 above. N_2O emission factors for composting are listed in table 4-31.

4.4.2.2 Activity Data

Table 4-30. MCFs for Composting Solid Manure

Composting Method	MCF (%)		
	Cool Climate	Temperate Climate	Warm Climate
Manure composting—in-vessel	0.5	0.5	0.5
Manure composting—static pile	1	2	2.5
Manure composting—intensive windrow	0.5	1	1.5
Manure composting—passive windrow	1	2	2.5

Source: IPCC, 2019.

Table 4-31. Direct N_2O Emission Factors for Composting Solid Manure

Composting Method	Direct N_2O Emission Factor (kg N_2O N/kg N_{ex})
Composting—in-vessel	0.006
Composting—static pile (forced aeration)	0.010
Composting—intensive windrow	0.005
Composting—passive windrow	0.005

Source: IPCC, 2019.

Table 4-32. Nitrogen Loss Fractions for Volatilization and Leaching for Composting Solid Manure

Type of Storage	Swine		Dairy Cow		Poultry		Other Cattle		Other Animals	
	%NH_3 N	%N_{leach}	%NH_3 N	%N_{leach}	%NH_3 N	%N_{leach}	%NH_3 N	%N_{leach}	%NH_3 N	%N_{leach}
Composting—in-vessel	60	0	45	0	60	0	60	0	18	0
Composting—static pile (forced aeration)	65	6	50	6	65	6	65	6	20	6
Composting—intensive windrow	65	6	50	6	65	6	65	6	20	6
Composting—passive windrow	60	4	45	4	60	4	60	4	18	4

Source: IPCC, 2019.

4.4.2.3 Ancillary Data

To estimate the daily CH_4 emissions from composting, the following information is needed:

- Animal type
- Animal population
- Temperatures (local ambient temperature and manure temperature)
- Total nitrogen in manure

4.4.2.4 Limitations and Uncertainty

A limitation of the GHG estimation method for manure composting is that it does not consider other organic carbon sources that might be added into manure composting. See appendix 4-B.8.2 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.4.3 CH_4 and N_2O From Aerobic Lagoons

Method for Estimating Emissions From Manure Storage and Treatment—Aerobic Lagoons

Methane

- The MCF for aerobic treatment is negligible and is designated as zero percent in accordance with the IPCC guidance.

Nitrous Oxide

- The IPCC Tier 2 method is used with IPCC emission factors.
- The method considers the volume of the lagoon and the total nitrogen content of the manure.

4.4.3.1 Description of Method

The IPCC Tier 2 methodology is provided for estimating CH_4 and N_2O emissions from aerobic lagoons. This methodology uses a combination of IPCC and country-specific emission factors from the U.S. EPA GHG Inventory. Aerobic conditions result in the oxidation of carbon to CO_2, not the reduction of carbon to CH_4, so CH_4 emissions from aerobic lagoons are considered negligible. The method for calculating N_2O emissions accounts for the volume of the lagoon as well as the total nitrogen content of the manure. Review considerations for total animal production emissions in box 4-1.

Methane

The MCF for aerobic treatment is negligible and was designated as zero percent in accordance with the IPCC (2019).

Nitrous Oxide

The IPCC Tier 2 approach is adapted to estimate N_2O emissions from aerobic lagoons (equation 4-31). The N_2O conversion factors for different aeration systems are listed in table 4-33.

Table 4-33. Direct N_2O Emission Factors (EF_{N2O}) for Aerobic Lagoons

Aeration Type	Direct N_2O Emission Factor (kg N_2O N/kg N_{ex})
Natural aeration	0.01
Forced aeration	0.005

Source: IPCC, 2019.

Table 4-34. Nitrogen Loss Fractions for Volatilization and Leaching for Aerobic Lagoons

Type of storage	Swine		Dairy Cow		Poultry		Other Cattle		Other Animals	
	%NH_3 N	%N_{leach}	%NH_3 N	%N_{leach}	%NH_3 N	%N_{leach}	%NH_3 N	%N_{leach}	%NH_3 N	%N_{leach}
Natural aeration	—	—	—	—	—	—	—	—	—	—
Forced aeration	85	0	85	0	—	0	85	0	27	0

Source: IPCC, 2019. There are no data available for natural aeration or forced aeration for poultry.

4.4.3.2 Activity Data

No activity data are needed for the estimation of CH_4 emissions from aerobic lagoons (MCF = 0). To estimate daily N_2O emissions, the following information is needed:

- Total nitrogen content of the manure (TNstorage)

4.4.3.3 Limitations and Uncertainty

See appendix 4-B.8.2 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.4.4 CH_4 and N_2O From Anaerobic Lagoons, Runoff Holding Ponds, and Storage Tanks

Method for Estimating Emissions From Manure Storage and Treatment—Anaerobic Lagoons, Runoff Holding Ponds, Storage Tanks

Methane

- The IPCC Tier 2 method is used to estimate CH_4 emissions.

Solid-liquid separation impacts the potential emissions from other systems (e.g., anaerobic lagoons) as its use would remove total solids (and therefore VS) from those systems. Use a modified IPCC Tier 2 approach if solid-liquid separation units are used and ensure emissions are captured from solid systems, as described in section 4.4.1 or 4.4.2. See appendix 4-C.3 for gaps concerning nitrogen removal due to solid-liquid separation.

Nitrous Oxide

- Emissions are a function of the exposed surface area and U.S.-based emission factors.
- The NH_3-N lost from anaerobic lagoons, runoff holding ponds, and storage tanks is used to calculate the indirect N_2O emissions.

4.4.4.1 Description of Method

Methane

The IPCC Tier 2 approach is recommended to estimate CH_4 emissions and is described in equation 4-15 (IPCC, 2019). The data for maximum CH_4 producing capacity (B_0) and MCF are listed in table 4-11 and table 4-35. Alternatively, MCFs can be calculated using the "MCF Calculations Example Spreadsheet" from IPCC (2019). Calculate VS using equation 4-16 (IPCC, 2019), where parameters are based on individual animal categories and productivity systems. Typical VS excretion in different animal manures is presented in table 4-26. Review considerations for total animal production emissions in box 4-1.

If there is a manure solid-liquid separation system in place prior to final manure storage, estimate the amount of solids (VS) removed from the manure stream and use equation 4-32 to estimate CH_4 emissions. Table 4-36 presents average values (or ranges) for different animal classes and separation technology. However, separation efficiency is highly dependent on the characteristics of the manure, screen size, total solid concentrations of the manure stream and the loading rate. If on-farm separation efficiencies are known, those values should be used. Alternatively, more detailed information can be found in the USDA National Resources Conservation Service (NRCS) Part 637 *Environmental Engineering National Engineering Handbook*. Nitrogen removal via solid-liquid separation is currently not addressed in these methods; see appendix 4-C.3 for gaps concerning nitrogen removal.

Equation 4-32: Modified IPCC Tier 2 Approach for Estimating CH_4 Emissions From Manure in Anaerobic Lagoon, Runoff Holding Ponds, and Storage Tanks With Solid-Liquid Separation

$$CH_4 = VS \times \left(\frac{100\% - \%VS}{100}\right) \times B_0 \times 0.67 \times \frac{MCF}{100}$$

Where:

CH_4	=	daily CH_4 emissions (kg CH_4/day)
VS	=	volatile solids (kg/day), use equation 4-16
$\%VS$	=	percent of VS removed via solid-liquid separation. Use table 4-36, or if not used, assume 0%.
B_0	=	maximum CH_4 producing capacity for manure (m^3 CH_4/kg VS)
MCF	=	methane conversion factor for the manure management system (%)
0.67	=	conversion factor of m^3 CH_4 to kg CH_4

Nitrous Oxide

N_2O emissions from liquid manure storage typically represent a relatively small portion of the N_2O emissions from farms. Most studies indicate the criticality of the crust for the formation and emission of N_2O (Petersen and Sommer, 2011). The crust allows air to be retained on the surface which, as ammonia diffuses through the crust, increases the potential for nitrification and denitrification due to microbial activity (Hansen et al., 2009; Nielsen et al., 2010). When a crust does not form, oxygen is not retained on the liquid surface with nitrogenous compounds, and therefore no N_2O is formed and emitted. Therefore, N_2O emissions from liquid manure storage are estimated as a function of the exposed surface area of the manure storage and the presence of a crust on the surface (equation 4-33), and the emission factor for N_2O depends on crust formation on the liquid storage. Use equation 4-17 and equation 4-18 for direct and indirect N_2O emissions, respectively, from anaerobic digesters. The emission factors of N_2O for different liquid storage methods are listed in table 4-37. Review considerations for total animal production emissions in box 4-1.

Equation 4-33: IPCC Tier 2 Approach for Estimating N_2O Emissions From Anaerobic Lagoon, Runoff Holding Ponds, and Storage Tanks

$$E_{N2O} = EF_{N2O} \times \frac{A_{surface}}{1{,}000}$$

Where:

E_{N2O}	=	daily nitrous oxide emissions (kg N_2O/day)
EF_{N2O}	=	N_2O emission factor (g N_2O-N/m^2/day)
$A_{surface}$	=	exposed surface area of the lagoon/pond/tank (m^2)
1,000	=	conversion factor for grams to kilograms (1 kg/1,000 g)

4.4.4.2 Activity Data

Table 4-35. MCFs for Liquid Storage

Housing Type	Storage Time	MCFs (%) Cool Temperate Moist (4.6°C)[a]	Cool Temperate Dry (5.8°C)[a]	Warm Temperate Moist (13.9°C)[a]	Warm Temperate Dry (14.0°C)[a]	Tropical Montane (21.5°C)[a]	Tropical Wet (25.9°C)[a]	Tropical Moist (25.2°C)[a]	Tropical Dry (25.5°C)[a]
Holding pond/storage tank	1 month	6	8	13	15	25	38	36	42
	3 months	12	16	24	28	43	61	57	62
	4 months	15	19	29	32	50	67	64	68
	6 months	21	26	37	41	59	76	73	74
	12 months	31	55	64	41	73	80	80	80
Uncovered anaerobic lagoon	N/A	60	67	73	76	76	80	80	80
Anaerobic digester, low leakage,[b] high quality gastight storage, best complete industrial technology	N/A	1							
Anaerobic digester, low leakage, high quality industrial technology, low quality gastight storage technology	N/A	1.41							
Anaerobic digester, low leakage, high quality industrial technology, open storage	N/A	3.55		4.38		4.59			
Anaerobic digester, high leakage, low quality technology, high quality gastight storage technology	N/A	9.59							
Anaerobic digester, high leakage, low quality technology, low quality gastight storage technology	N/A	10.00							
Anaerobic digester, high leakage, low quality technology, open storage	N/A	12.14		12.97			13.17		

[a] Values represent average annual temperature.

[b] Leakage rate of the gastight storage (with $0 \leq L_{sto,gt} \leq 1$ m^3 m^{-3}). For high quality gastight storage of the digestate $L_{sto,gt}$ is assumed to be 0.01 m^3 m^{-3}. For low quality gastight storage of the digestate, $L_{sto,gt}$ is assumed to be 0.1 m^3 m^{-3}. For open storage of the digestate, $L_{sto,gt}$ is assumed to be 1.0 m^3 m^{-3}.

Source: IPCC, 2019.

Table 4-36. Total Solids Removal Efficiency of Select Manure Separation Systems

	Separation Efficiency (%VS) by Livestock Class (%)			
	Dairy	Beef	Swine	Poultry
Sloped screen, static	30–60	30–50	10–60	24–60
Slope screen, vibrating	50–70	—	30–60	—
Rotary drum	25	—	—	—
Screw press	25–50		16	—
Belt press	50	16	20–60	—
Roller press	24	—	—	—
Centrifuge	50	50	30–60	—

Sources: Williams et al., 2020; USDA NRCS, 2019.

Table 4-37. Direct N_2O Emission Factors for Liquid Storage With Different Crust Formation

Type of Liquid Storage	Units	EF_{N2O}	Associated Equation
Uncovered liquid manure without crust	g N_2O/m^2/day	0	Equation 4-33 and equation 4-18
Uncovered liquid manure with crust	g N_2O/m^2/day	0.8	Equation 4-33 and equation 4-18
Covered liquid manure	g N_2O/m^2/day	0	Equation 4-33 and equation 4-18
Anaerobic digester	kg N_2O/kg N_{ex}	0.0006	Equation 4-17 and equation 4-18

Source: Rotz et al., 2011; Olesen et al., 2006; Külling et al., 2003; Sneath et al., 2006; IPCC, 2019.

Table 4-38. Nitrogen Loss Fractions for Volatilization and Leaching for Liquid Storage

Type of Storage		Swine		Dairy Cow		Poultry		Other Cattle		Other Animals	
		$\%NH_3$ N	$\%N_{leach}$	$\%NH_3$ N	$\%N_{leach}$	$\%NH_3$ N	$\%N_{leach}$	$\%NH_3$ N	$\%N_{leach}$	$\%NH_3$ N	$\%N_{leach}$
Uncovered Anaerobic lagoon		40	0	35	0	40	0	35	0	35	0
Anaerobic digester[a]		5–50	0	5–50	0	5–50	0	5–50	0	5–50	0
Liquid/slurry	Uncovered liquid manure without crust	48	0	48	0	40	0	48	0	15	0
	Uncovered liquid manure with crust	30	0	30	0	-	0	30	0	9	0
	Covered liquid manure	10	0	10	0	8	0	10	0	3	0

Source: IPCC, 2019.

[a] IPCC (2019) notes "Nitrogen losses from digestate storage strongly depend on the digestate composition and on the storage cover. Digestate with a low dry matter content and no cover can [lose] up to [50%] of nitrogen. The lower range of [5%] losses is valid for digestate with a high dry matter content and a cover. The ranges indicated also apply to co-digestates. It is advised to use, the liquid slurry without cover for uncovered digestate."

4.4.4.3 Ancillary Data

To estimate daily CH_4 and N_2O emissions from liquid manure storage, the following information is needed:

- Animal type
- Animal population
- Temperatures (local ambient temperature or manure temperature)
- The exposed surface area of the manure storage

4.4.4.4 Limitations and Uncertainty

See appendix 4-B.8.2 for current available default uncertainty bounds and appendix 4-C.4 for a brief discussion of uncertainty data gaps/limitations.

4.4.5 CH_4 From Anaerobic Digesters With Biogas Utilization

Method for Estimating Emissions From Manure Storage and Treatment—Anaerobic Digesters With Biogas Utilization

Methane

- Use the IPCC Tier 2 method, with Clean Development Mechanism emission factors for digester types, to estimate CH_4 leakage from digesters.
- Anaerobic digester systems convert organic matter in manure into CH_4 and subsequently combust CH_4 into CO_2.
- Gas leakage from digesters is the main source of GHG emissions.
- Leakage of CH_4 from the anaerobic digester system is estimated.

Nitrous Oxide

- N_2O leakage from digesters is negligible.

4.4.5.1 Description of Method

Since an anaerobic digestion system converts organic carbon in manure into CH_4 and subsequently combusts CH_4 into CO_2, the GHG emissions from manure anaerobic digestion operation are mainly from the leakage of digesters. The leakage of CH_4 can be estimated based on the IPCC Tier 2 approach in combination with technology-specific emission factors. Review considerations for total animal production emissions in box 4-1.

Methane

Equation 4-34 describes the IPCC Tier 2 approach for estimating CH_4 emissions for anaerobic digesters. The CH_4 generated from digesters is assumed to be flared or used as the biogas for electricity generation; the only emissions from digesters are from system leakage. The B_0 values are obtained from IPCC (2019) and are listed in table 4-25. The emission factors for the fraction of CH_4 leaked from the digestion are listed in table 4-39. Estimate the VS data using equation 4-16.

Equation 4-34: IPCC Tier 2 Approach for Estimating CH_4 Emissions From Anaerobic Digesters

$$E_{CH4} = VS \times B_0 \times 0.67 \times \frac{EF_{CH4\ leakage}}{100}$$

Where:

E_{CH4}	=	daily CH_4 emissions (kg CH_4/day)
VS	=	volatile solids (kg VS/day)
B_0	=	maximum CH_4 producing capacity for manure (m^3 CH_4/kg VS)
$EF_{CH4\ leakage}$	=	emission factor for the fraction of CH_4 leaked from the digestion (%)
0.67	=	conversion factor of m^3 CH_4 to kg CH_4

4.4.5.2 Activity Data

Table 4-39. Emission Factors for the Fraction of CH_4 Leaking From Digesters

Digester Configurations	$EF_{CH4\ leakage}$ (%)
Digesters with steel or lined concrete or fiberglass digesters with a gas holding system (egg-shaped digesters) and monolithic construction	2.8
UASB-type digesters with floating gas holders and no external water seal	5
Digesters with unlined concrete/ferrocement/brick masonry arched-type gas holding section; monolithic fixed-dome digesters	10
Other digester configurations	10

Source: CDM, 2012.

4.4.5.3 Ancillary Data

To estimate daily CH_4 leakage from anaerobic digestion, the following information is needed:

- Animal type
- Animal population
- Digester configurations

4.4.5.4 Limitations and Uncertainty

See appendix 4-B.8.2 for current available default values and appendix 4-C.4 for a brief discussion of uncertainty data gaps.

4.5 Available Nitrogen for Land Application

In the case where manure is land applied, whether directly on pasture or removed from housing or manure storage and treatment and subsequently applied, use the following equations to determine the nitrogen available for land application and then consult chapter 3 to determine subsequent emissions. The calculation is based on IPCC (2019), and considers nitrogen lost to emissions, nitrogen added (from organic forms of bedding such as straw, sawdust, wood chippings) and nitrogen removed (e.g., to be used for feed, fuel, or construction). The nitrogen removed should be estimated by the entity based on other uses of manure or litter.

Equation 4-35: Available N for Land Application

$$N_{available} = [(N_{ex} \times 365) \times (1 - N_{lost})] + BeddingN - ([N_{ex} \times 365 + (BeddingN)] \times N_{removed})$$

Where:

$N_{available}$	=	managed manure N available for land application, by system (kg N/year)
N_{ex}	=	total nitrogen excretion (kg N/head/day)
365	=	days in year (days/year)
N_{lost}	=	N lost via direct emissions, NH_3 volatilization, and leaching, see equation below (fraction)
BeddingN	=	additional nitrogen from bedding material for all animals managed on the system (kg N/year)
$N_{removed}$	=	N removed from the system prior to land application (fraction)

$$N_{lost} = EF_{N2O} + (EF_{N2O} \times R_{N2(\mathrm{N2O})}) + \frac{\%NH_3}{100} + \frac{\%Nleach}{100}$$

Where:

N_{lost}	=	N lost via direct emissions, NH_3 volatilization, and leaching (fraction)
EF_{N2O}	=	direct N_2O emission factor (kg N_2O-N/kg N)
$R_{N2(N2O)}$	=	Ratio of N_2:N_2O emissions, the default value is 3 (kg N_2-N/kg N_2O-N)
$\%NH_3$	=	percentage of N_{ex} lost as NH_3-N in animal housing
%Nleach	=	percentage of N_{ex} lost as N leaching in animal housing. If no data are available, assume 0.

$$BeddingN = Bedding\ Factor \times Pop$$

Where:

BeddingN	=	additional nitrogen from bedding material for all animals managed on the system (kg N/year)
Bedding Factor	=	additional nitrogen from organic forms of bedding material, (kg N/head/year), see table 4-40.
Pop	=	number of animals (head)

Table 4-40. Bedding and Feed Loss Factors

Animal Type	Housing or Manure Storage and Treatment	Bedding (kg N/Head/Year)
All	Pasture	0
Poultry	Anaerobic lagoon	0
Poultry	With and without litter, and solid storage	0
Market swine	Liquid systems, solid storage	0.8
Breeding swine	Liquid systems, solid storage	5.5
Dairy cow	Liquid systems, solid storage, dry lot	7
Dairy heifer	Dry lot	7
Horses, mules & ass, goats, sheep, On feed cattle	Dry lot	4

Source: IPCC, 2019.

4.6 Chapter 4 References

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Appendix 4-A: Animal Production Systems

This section discusses the production systems for beef and dairy cattle, sheep, swine, and poultry, and provides the background necessary for understanding sections 4-A.2 through 4-A.3, which cover GHG emissions from these systems.

4-A.1 Dairy Production Systems

4-A.1.1 Overview of Dairy Production Systems

The U.S. dairy production system features several key processes for dairy cattle, their manure, and their end products (meat, milk), as shown in figure 4A-1. This conceptual model provides an overview of the typical dairy system, following cattle from birth to slaughter and following manure from the animal through a management system. Manure is produced during each stage and is managed differently depending on location. Its management has implications for the quantity of GHG emissions and sinks. The estimation methods include emissions estimates from enteric fermentation, housing, and manure management; however, they do not constitute a full LCA.

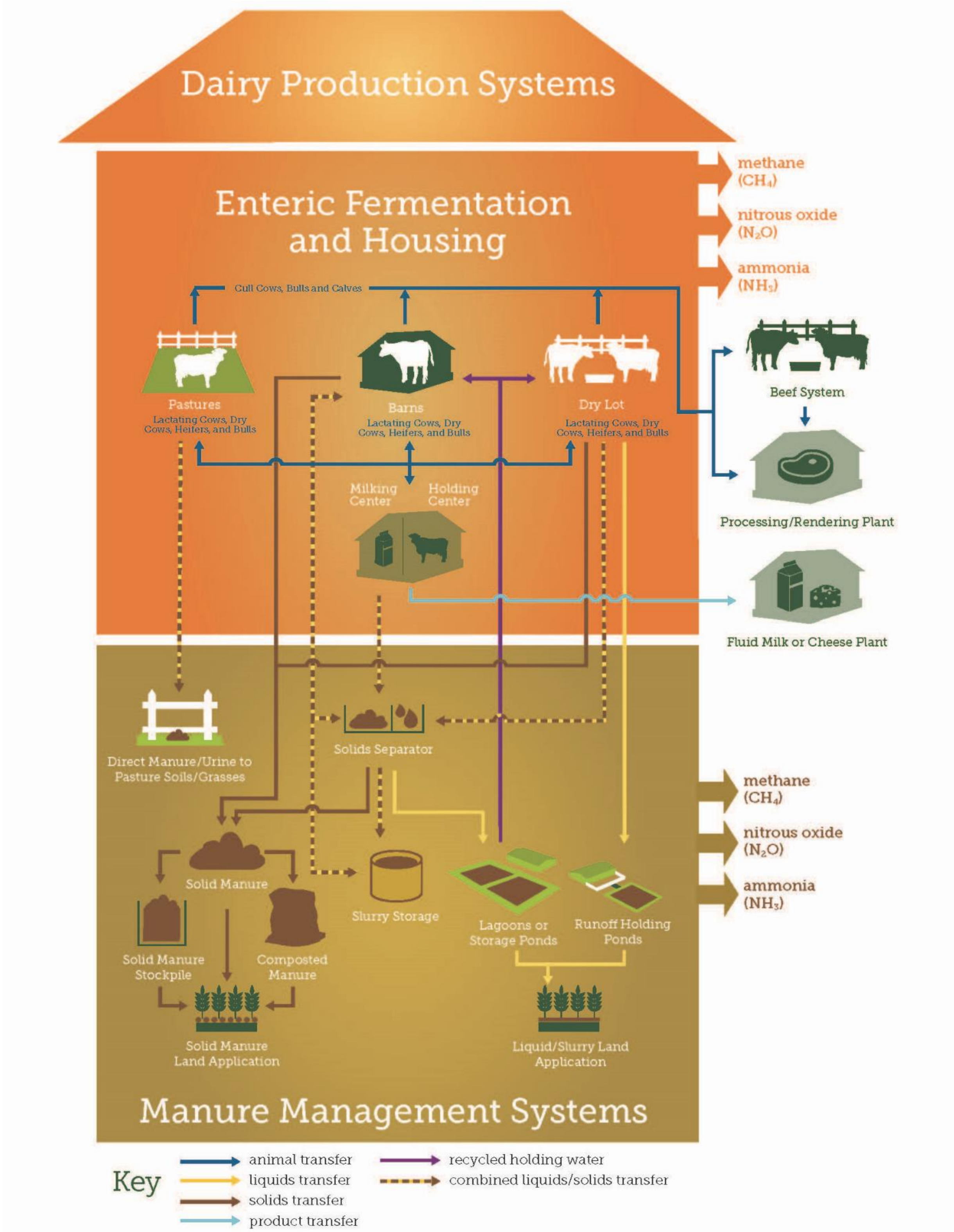

Figure 4A-1. Conceptual Model of Dairy Systems in the United States

4-A.1.2 Dairy Diets, Housing, and Manure Handling

Two general dairy farm types can be distinguished in the United States: confinement feeding systems (including barns and dry lots) and pasture-based systems (USDA, 2004). Typical housing systems for confinement feeding operations include tie stall barns, compost barns, freestall barns, freestall barns with dry lot access, and dry lots. Dry lot systems house animals in pens similar to beef cattle feedlots, but at a lower stocking density. In pasture-based systems, cattle graze pasture for periods of time based on feed availability and environmental conditions, but are housed in barns/dry lots and fed stored feed when pasture is not available. The dairy cattle life cycle production phase is generally divided into three segments: growing animals (calves and replacement heifers), lactating mature cows, and dry mature cows. Nutrient needs, and therefore diets, and intake are very different between the different life cycle phases. Housing and manure management systems vary considerably throughout the country and can differ within a region and by the size of the herd. In cases where housing and manure management varies by animal group (e.g., heifers, nonlactating cows, and lactating cows), estimates of GHG emissions from one group are not applicable to other groups. When housing and manure management are similar between groups (e.g., all cattle on dry lots), diet and intake adjustment factors can be used to compare GHG emissions for the different groups.

Manure and soiled bedding from barns can be handled in a number of ways. Manure can be removed from the barns mechanically and directly loaded into manure spreaders, although this is not common on medium and large farms. Manure and bedding may be managed as a compost within the barn via regular mechanical turning, while deep-bedded systems with no composting may be cleaned out and their manure stored as solid stacks or composted before land application. Manure with a lower solids content may be stored in a tank or pit as a slurry or transported to a solid–liquid separation system with the liquid fraction conveyed (pumped or by gravity) to a long-term wastewater storage pond, while the solids can be dewatered naturally and reused as bedding, composted, land-applied, and/or sold.

Liquid manure can also be processed in an anaerobic digester, where bacteria break it down to produce biogas that can be flared or captured for energy purposes before storage of digester effluent. In dry lot systems, the manure is typically stacked within or near the lots, then either land-applied or composted. Lot runoff and milking parlor wash water is typically pumped to a wastewater storage pond. Some dry lot dairies use flush systems to clean manure from alleyways behind the feed bunks; this washwater is eventually stored in a wastewater storage pond. Open freestall dairies have a combination of barns with exercise yards between the barns, so they handle manure similarly to traditional freestall barns and dry lot production systems. Wastewater from milking centers (manure, clean-in-place water, and floor washdown water) is typically combined with barn manure and stored in wastewater storage ponds or lagoons; in many cases this liquid goes through a solid–liquid separation process first. In pasture-based systems, manure is deposited directly onto the pasture and therefore not intensively managed, but may accumulate in areas where animals tend to congregate (e.g., watering areas, shade).

4-A.2 Beef Production Systems

4-A.2.1 Overview of Beef Production Systems

The U.S. beef production system has several key components for cattle, their waste, and their end products, as depicted in figure 4A-2. This conceptual model provides an overview of the typical beef processing systems, following the segments of the beef cattle industry (i.e., cow-calf, stocker, feeder/finisher, and packer) from birth to slaughter and following waste from the animal through a management system. Waste is produced during each stage of activity in the system and is managed differently depending on location.

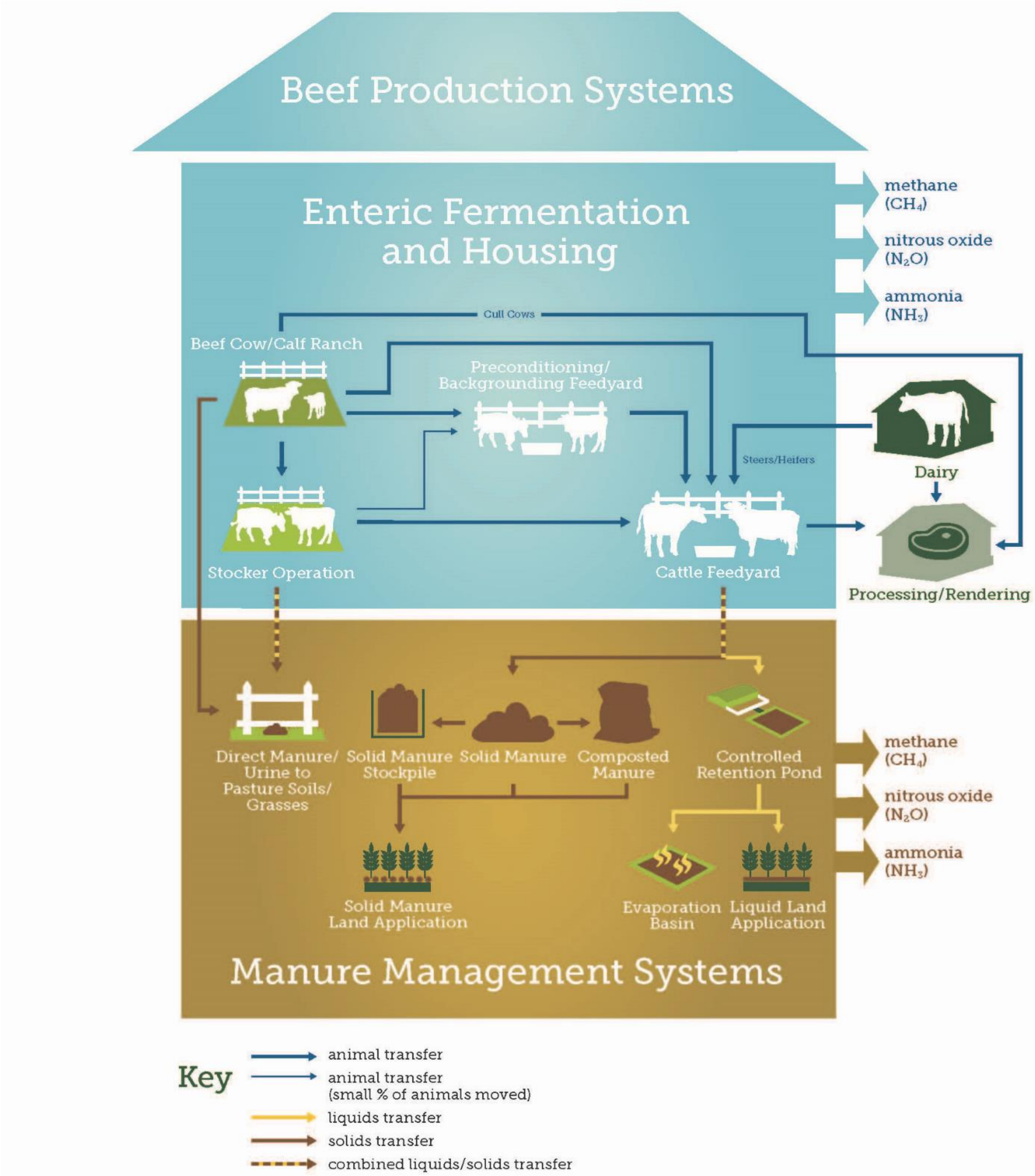

Figure 4A-2. Conceptual Model of Beef Production Systems in the United States

4-A.2.2 Beef Cattle Diets, Housing, and Manure Handling

Cow-Calf Operations and Bulls

Cow herds and replacement heifers are most often housed on pasture. They deposit feces and urine on pastures and rangeland, which may be concentrated in areas in which feeding or watering takes place. A methodology for estimating CH_4 emissions from pasture and rangeland is included in chapter 4, but the N_2O emission methodology is included as part of the croplands system because of the manure's influence on carbon stock changes in a process-based model (see chapter 3). Under severe drought conditions, beef cows may be moved to confinement operations and fed diets based primarily on byproducts. However, only a small percentage of the U.S. beef cow herd undergoes this confined feeding.

Stockers

Stocker cattle are usually housed on pasture. A methodology for estimating CH_4 emissions from pasture and rangeland is included in chapter 4, but the N_2O emission methodology is included as part of the croplands system because of the manure's influence on carbon stock changes in a process-based model (see chapter 3). Weaned calves from the cow-calf segment are used as stocker cattle and can be housed for short periods of time in dry lots before being moved to grazing pasture.

Feedlot Cattle

Housing and manure management at most beef cattle feeding operations differ greatly from those used in other animal species, with the vast majority being finished in dry lot pens with soil surfaces. Manure is normally deposited on the pen surface and scraped from the pens after each lot of cattle goes to market. Part of the manure may be stacked in the pen to provide mounds that improve pen drainage and ensure that cattle have a dry place to lie after rains. Manure removed from the pen may be immediately applied to fields near the feedlot, stockpiled for later use, or composted in windrows. Manure scraped from the pens normally has a moisture content of 30 to 50 percent and may contain some soil from the pen. Runoff from pens is normally collected in retention ponds. Settling basins may be used to limit the quantity of manure solids and soil particles that reach the retention pond.

In the northern United States, and in areas with high rainfall, cattle may be fed in naturally ventilated barns with slotted floors for collection of urine and feces or in deep-bedded barns with concrete floors in which the manure and bedding (normally straw or stalks) accumulates during the feeding period (Spiehs et al., 2011). Adding bedding will increase the quantity of carbon (and possibly nitrogen) available to be metabolized by microbes possibly enhancing emissions. These confined facilities are characterized by the absence of runoff control systems.

4-A.3 Sheep Production Systems

4-A.3.1 Overview of Sheep Production Systems

There are 102,000 sheep and lamb operations in the United States, with an inventory of 5.27 million sheep and lambs as of January 1, 2017 (USDA NASS, 2021). Most breeding flocks are small and consist of less than 100 head of ewes. The lamb feeding industry is also diverse in size, with small feedlots located throughout the farm flock areas and large feeding operations located in close proximity to local grain production capacity (Shiflett, 2011).

4-A.3.2 Sheep Diets, Housing, and Manure Handling

Lambing season may occur at various times of the year, depending on production objectives, feed resources, environmental conditions, and market targets. When lambing occurs, in January through March, ewes are generally housed in bedded barns. Bedding is removed and spread after animals are turned out on pasture. Ewes are generally bred on pasture in September through November and, depending on weather, will be moved into barns before lambing—or earlier as forage availability and weather dictate.

Pasture lambing is another farm flock production system that is used to maximize nutrients provided by grazed forages. In this case the ewe is bred in November or December to lamb on pasture in April or May. Lambs are weaned at about 120 days and 32 kilograms and may be sent to the feedlot or finished on grass. Ewes are not fed grain, and harvested forage is provided only when growing seasons and weather dictate. These flocks will be housed in bedded barns only when they need protection from winter weather.

Sheep feedlots are primarily dry lots, and manure is scraped from the pens as in beef cattle feedlots.

4-A.4 Swine Production Systems

4-A.4.1 Overview of Swine Production Systems

The conceptual model of the U.S. swine production system (figure 4A-3) provides an overview of typical production systems, following animals from birth to harvest and following manure from the animal through a management system. Manure is produced during each stage of production in the system and is managed differently depending on location, which has implications for the quantity of GHG emissions.

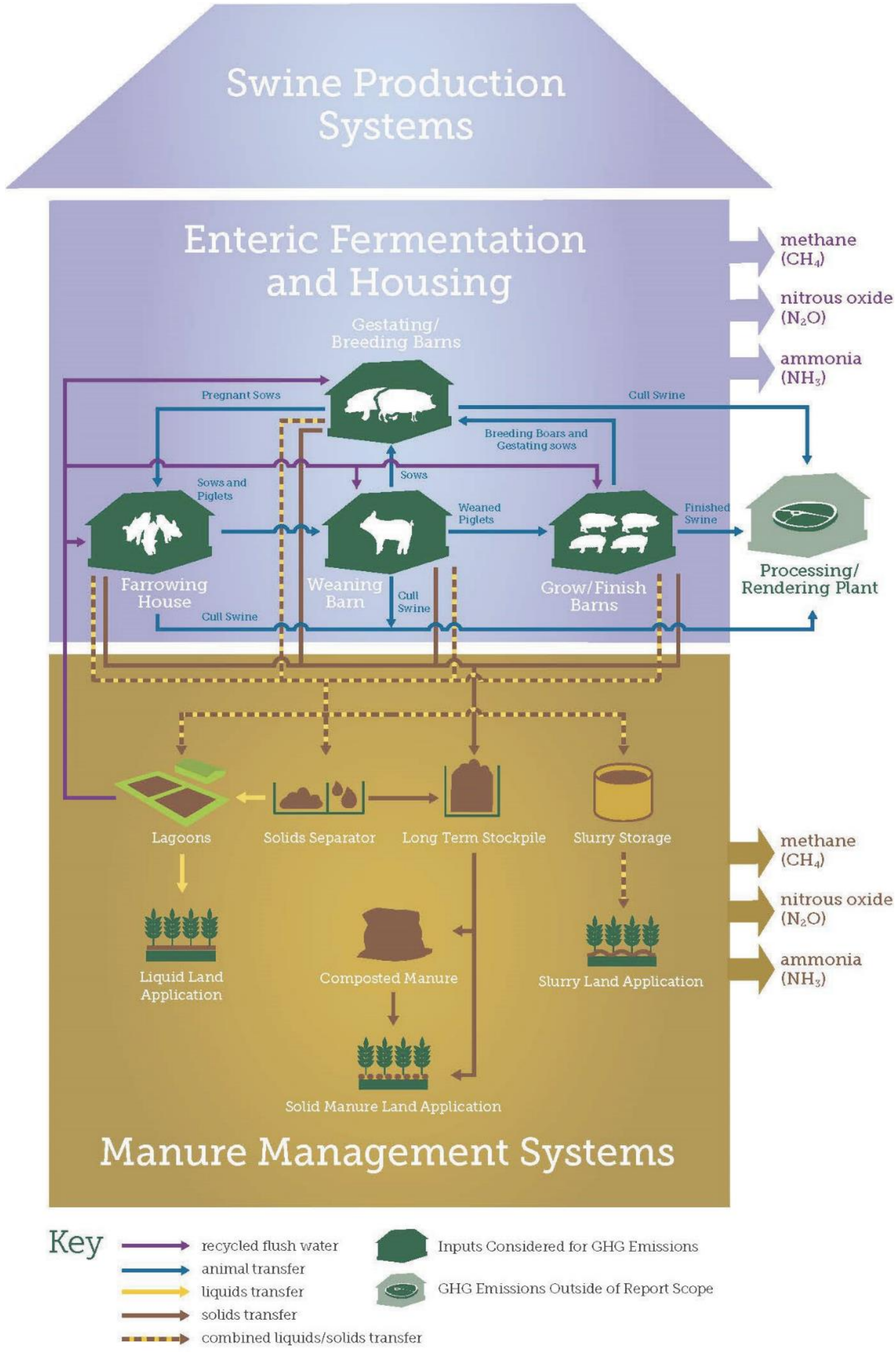

Figure 4A-3. Conceptual Model of Swine Production Systems in the United States

4-A.4.2 Swine Housing and Manure Handling

The manure management systems associated with production operations all have the basic elements of collection, storage, treatment, transport, and utilization. Most swine facilities handle manure as a slurry either within the building (deep pit finishing barns or shallow pit nurseries, gestation or finishing barns) or in outside storage (pull-plug systems for nurseries, sows, or finishing pigs). The manure is generally stored under the facility, discharged to a separate storage tank, or flushed to an anaerobic lagoon. In the case of in-house manure storage, little water is added to the storage structure, and anaerobic conditions prevail with little biological processing of manure taking place. Outside storage structures that contain slurry with little dilution water offer minimal biological treatment as well. However, lagoon systems where manure is flushed from housing and additional dilution water is added offer more treatment. Dry systems or deep-bedded systems are much less common. They are mainly used for sow or finishing production, in which case bedding material, often straw, is provided and manure plus bedding is handled as solid material, sometimes composted.

4-A.5 Poultry Production Systems

4-A.5.1 Overview of Poultry Production Systems

The U.S. poultry production system features several key processes for poultry, their manure/litter, and their end products (meat, eggs), as shown in figure 4A-4. The figure provides an overview of the typical production systems, following both the layer and broiler phases. It follows birds from birth to slaughter and follows manure from the animal through a management system. Manure is produced during each stage of activities in the system and is managed differently depending on location.

The U.S. poultry industry is the world's largest producer and second largest exporter of poultry meat. The United States is also a major egg producer. The poultry and egg industry are a major feed grain user, accounting for about 45.4 billion kilograms (100 billion pounds) of feed yearly.

The egg incubation period for a chicken is 21 days. Following hatch, broiler chickens are reared for 42 to 49 days (six to seven flocks per year), depending upon the market intent (e.g., roasters). U.S. egg operations produce more than 90 billion eggs annually. More than 75 percent of egg production is for human consumption (the table-egg market). The remainder of production is for the hatching market. These eggs are hatched to provide replacement birds for the egg-laying flocks and to produce broiler chicks for grow-out operations. Following a 16- to 22-week growth period, hens start laying eggs.

The U.S. turkey industry produces more than one-quarter of a billion birds annually, with the live weight of each bird averaging more than 25 pounds. The egg incubation period for a turkey is 28 days. Following hatch, turkey poults are reared for 15 to 22 weeks (one to three flocks per year) depending on the market intent (e.g., roasters).

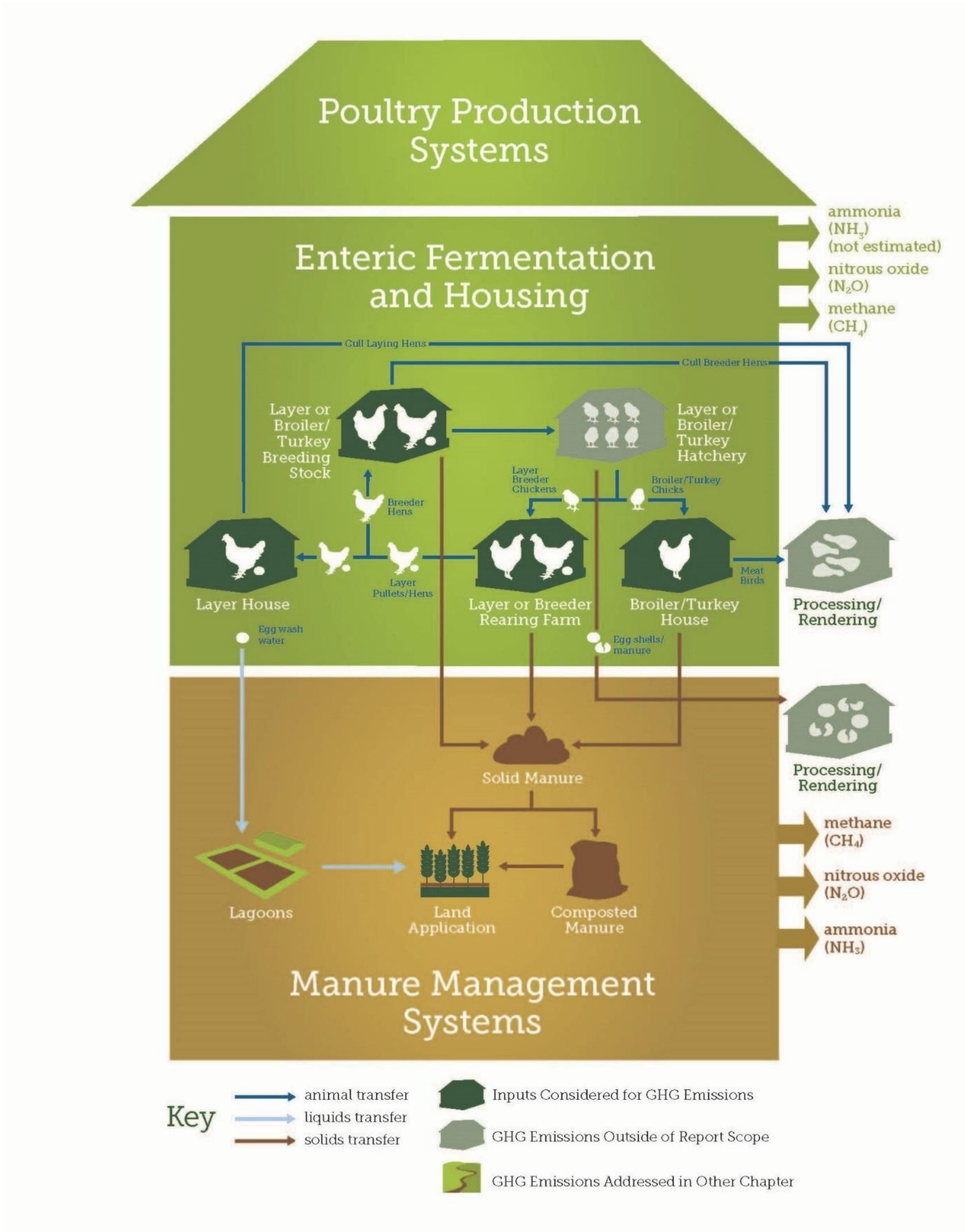

Figure 4A-4. Conceptual Model of Poultry Production Systems in the United States

4-A.5.2 Poultry Housing and Manure Handling

The vast majority of the industry raises birds on litter in mechanically ventilated or naturally ventilated houses. Reuse of litter and number of flocks grown on the same litter is variable across the country and can range from as low as a single flock to as many as 18 flocks on the same litter source. Litter dry matter content can vary from 40 to 80 percent, depending on management.

Laying hen and pullet housing types range from high-rise houses, where hens are in cages and manure accumulates in a basement under the cages and is removed annually, to a manure-belt house where hens are in cages and manure is removed daily or more frequently from the basement to an external shed and stacked before periodic removal for land application (once or twice per year), to aviaries where hens are raised on litter (in large rooms as opposed to cages) that is removed from the aviary annually or more frequently. When manure is removed from the house it may be immediately applied to fields, stockpiled, or composted. Moisture content may vary from 80 percent moisture down to 20 percent moisture (aviaries).

4-A.6 Background on Enteric Fermentation CH_4 Emissions

CH_4 is a normal byproduct of anaerobic fermentation of carbohydrates and proteins in the foregut of ruminants and the hindgut of ruminants and nonruminants. The microbiology, physiology, and biochemistry of enteric fermentation CH_4 production have been reviewed (Beauchemin et al., 2020; NASEM, 2016; Thompson and Rowntree, 2020) and summaries are available in those articles and will not be covered in this overview. Factors affecting enteric CH_4 emissions, and potential mitigation strategies to decrease enteric CH_4 (Beauchemin et al., 2020; Hristov et al., 2013a, 2013b; Hunerberg et al., 2015; Ouatahar et al., 2021) emissions are reviewed below in section 4-A.6.4. Hammond et al. (2016) reviewed methods to measure enteric CH_4 emissions from individual animals or groups of ruminants; their findings are briefly summarized below.

4-A.6.1 Methods for Measuring Enteric CH_4

Individual Animals

The standard method of measuring CH_4 emissions from ruminants is by respiration calorimetry (oxygen(O_2), CO_2, and CH_4 sensors) or environmental chambers (CO_2 and CH_4 sensors only). Other techniques, including head boxes, internal tracers, micrometeorology, isotope dilution, and polyethylene tunnels, have also been used (Cole et al., 2018; Harper et al., 2011; Kebreab et al., 2006). More recently, several new technologies have been developed to measure individual animal emissions. To address the difficulty in measuring enteric CH_4 emissions while cattle graze pasture, alternate methods are being sought and developed. As one example, Goopy et al. (2011) has proposed a portable static chamber method to measure daily CH_4 production. Until validated, results using alternate methods should be viewed with caution.

A variety of respiration chambers have been developed to measure enteric CH_4 losses, total energy metabolized, or both, by the animal. In general, air is pulled from the chamber at a known rate and replaced with outside air. Flow of air and concentrations of CH_4, CO_2, and O_2 are measured in the air entering and leaving the chamber to determine total CO_2 and CH_4 production and O_2 consumption by difference. When properly calibrated and used, respiration chambers give highly accurate, precise measurements. However, they are expensive to build and operate and require significant knowledge, skill, and labor.

Feed intake and production is usually decreased while animals are in chambers and the measurements do not necessarily reflect intake and production from typical commercial systems.

This limitation can be partially overcome by feeding animals at different levels of intake and measuring the effects. Head boxes use the same principles as respiration chambers and have many of the same limitations. In-barn chambers using drop-down curtains have been used to measure NH_3, CH_4, and other gases emitted from groups of dairy cows at relatively lower cost than chambers (Aguerre et al., 2011; Powell et al., 2007, 2008).

Internal tracer techniques such as the sulfur hexafluoride (SF_6) tracer method (Johnson et al., 1994) were developed to allow measurements of CH_4 emissions by free-ranging animals, such as those grazing pasture, or when real-world levels of feed intake are needed that occur with large pens. The limitations to this method are the need for trained animals, the need for larger sample sizes (compared with chambers) to detect the influence of mitigation techniques, and concerns about inconsistent releases of tracer gas from SF_6 permeation. Additionally, the SF_6 technique generally results in emissions estimates that are lower than chamber measurements, possibly because the SF_6 method does not measure all lower gut CH_4 production (McGinn et al., 2006). The advantages and shortcomings of the SF_6 method have been reviewed (Lassey et al., 2011).

To overcome the feed intake limitations of respiration chambers and to measure CH_4 emissions of grazing cattle, automated head chamber systems have been developed (i.e., GreenFeed by C-Lock™, Rapid City, South Dakota). These commercially available systems appear to give mean values similar to respiration chambers, although there is greater variability in individual animals because CH_4 is primarily emitted during eructation and emissions are measured for short time periods (5 minutes or less) several times daily and thus may not collect a representative sample of eructations (Cole et al., 2020a; Gunter and Bradford, 2017; Hammond et al., 2015). These systems have also been successfully employed to measure enteric CH_4 from confined dairy cattle (Hristov and Melgar, 2020). Proper calibration and maintenance (Gunter et al., 2017; Gunter and Beck, 2018) and adequate numbers of animals and readings (Arthur, 2017; Hammond et al., 2015; Hristov and Melgar, 2020; Jonker et al., 2016) are needed to obtain reliable results.

Group of Animals

Micrometeorology methods have been used extensively to measure CH_4 and NH_3 emissions from grazing land, whole feed yards, or portions of feed yards (pens, retention ponds, manure stockpiles, etc.). These methods have been reviewed (Flesch et al., 2005; Fowler et al., 2001; Harper et al., 2011). Laubach et al. (2008) compared the SF_6 method with three micrometeorological methods (integrated horizontal flux, flux gradient, and backward Lagrangian stochastic (bLS)) using steer grazing paddocks. In general, the micrometeorological methods yielded higher CH_4 emissions estimates than the SF_6 method, with a greater difference when animals were within 22 meters of the CH_4 sampler. This effect was especially true for the flux gradient method. The lower values for the SF_6 method could be due in part to the fact that the SF_6 method does not measure emissions from the lower gut or from fermentation of feces on the paddock surface.

Tomkins et al. (2011) compared enteric CH_4 emissions for steers grazing pasture using the bLS method and respiration chambers. Emissions estimated using the bLS model were slightly greater than with respiration chambers (136.1 vs. 114.3 g/head daily). However, emissions per gram of DMI were not different (29.7 vs. 30.1 g CH_4/kg DMI), suggesting that the bLS model may be suitable for estimating enteric CH_4 emissions for groups of cattle.

Most dispersion models and micrometeorological methods assume that emissions are uniformly distributed over the source area. In some cases, such as for individual cattle in a pen or field, this is untrue. Therefore, McGinn et al. (2011) developed a method that used a point-source dispersion model and measured atmospheric CH_4 concentrations using multiple open-path lasers to measure

CH_4 emissions from a paddock containing 18 cattle. Enteric CH_4 emissions did not differ from values measured using other techniques. However, recoveries of known CH_4 releases averaged only 77 percent using this method, and this method gave more reliable measurements during the daytime when atmospheric conditions were unstable, than at night when atmospheric conditions were stable.

Todd et al. (2019) measured enteric CH_4 emissions from beef cows on Oklahoma tall-grass prairie during three seasons using the McGinn (2011) point source dispersion model, the automated head chamber system, and eddy covariance. They concluded in their study that the point source dispersion model tended to overestimate enteric CH_4 emissions, whereas the automated head chamber system tended to underestimate emissions. Their study demonstrated the challenges in quantifying CH_4 emissions by grazing animals because of their mobility and dispersed behavior while grazing, and the dynamic interactions of forage quality, selective grazing, and diurnal variations in DMI.

In California, Frank Mitloehner (see Cooprider et al., 2011, and Stackhouse-Lawson et al., 2013) developed cattle pen enclosures that allowed for collection of GHG and other emissions from pens of beef or dairy cattle and estimations did not differ from respiration chambers. The emissions measured included both enteric and pen surface manure CH_4 emissions.

4-A.6.2 Background on Enteric Methane Emissions From Dairy Cattle

Enteric CH_4 production varies primarily with feed intake and is associated with production stage in dairy cattle, with the highest rates of feed intake and CH_4 emissions being produced by lactating cows (table 4A-1). This table illustrates, conceptually, the observed variation in dairy cattle at different stages of maturity and activity, but it is not intended to show absolute differences. Many factors affect enteric CH_4 production, and therefore altering dairy cattle diets could have an impact on enteric CH_4 production. However, the results in table 4A-1 clearly illustrate the difference in enteric CH_4 emissions; in particular, emissions from lactating dairy cattle are relatively higher than those from growing (i.e., heifers) and dry cattle. While there have been overall improvements in milk production with breeding programs, there is no evidence that any breed of dairy cow produces less enteric CH_4. Münger and Kreuzer (2008) measured enteric CH_4 production from Holstein, Simmental, and Jersey cows and found no persistent differences in CH_4 yields, with average enteric CH_4 being about 25 g CH_4/kg DMI.

Although the dairy industry is primarily composed of three animal types—growing (i.e., calves, replacement heifers), lactating cows, and nonlactating cows—most of the limited emissions research conducted to date has been targeted at lactating cows, which typically produce at least 50 percent more enteric CH_4 per head than other dairy cattle types. Few emissions data exist for calves, heifers, and nonlactating cows. Therefore, most of the information presented in this appendix focuses on lactating cows.

Table 4A-1. Examples of CH_4 Emissions Measured in Dairy Cattle

Animal Type	CH_4 Emissions	Method Used to Measure Emissions	Reference
Dairy cattle	260 g/animal/day	Calculated Blaxter and Clapperton (1965)	Crutzen et al. (1986)
Heifer, 6–24 months	140 g/LU/day		
Dairy cattle, dry period	139 g/LU/day	Respiration calorimetry	Holter and Young (1992)
Dairy cattle, lactating	268 g/LU/day		

Animal Type	CH_4 Emissions	Method Used to Measure Emissions	Reference
Dairy cattle	257 g/LU/day	Respiration calorimetry	Kirchgessner et al. (1991)
Dairy cattle, lactating	429 g/animal/day	Wind tunnel	Sun et al. (2008)
Dairy cattle, dry period	290 g/animal/day		
Dairy cattle, lactating	538–648 g/animal/day	Respiration calorimetry	Aguerre et al. (2011)

LU = livestock unit (500 kg)

4-A.6.3 Background on Enteric Methane Emissions From Beef Cattle

Because of differences in the diets, animal physiological state and age, and manure handling, the proportions and sources of GHG emissions differ among the cow-calf, stocker, and finishing segments of the beef cattle industry. The primary source of GHG emissions from the beef cattle industry is enteric CH_4, produced primarily in the rumen, although some CH_4 is also produced in the lower gut.

Beauchemin et al. (2010) used the Holos model (Little et al., 2008) to conduct an LCA of beef production in western Canada:

- Of total CO_2-eq, 63 percent was from enteric CH_4 (5 percent of emissions were from manure CH_4, 23 percent from manure N_2O, 4 percent from soil N_2O, and 5 percent from energy CO_2).
- 61 percent of CO_2-eq emissions were from the cow-calf herd, 19 percent were from replacement heifers, 8 percent were from backgrounding operations, and 12 percent were from feedlots.
- 79 percent of enteric CH_4 losses were from the cow herd, 3 percent from bulls, 2 percent from calves, 7 percent from backgrounders, and 9 percent from feedlots.
- N_2O contributions (CO_2-eq) as a percent of total GHG emissions were as follows: 2 percent for feedlot manure, 2 percent for feedlot soil, 2 percent for cow-calf herd soil, and 20 percent for cow-calf herd manure.

Cow-Calf Operations and Bulls

There is no evidence that any breed of beef cow produces less enteric CH_4 than another. A few reports suggest that efficient cattle (those selected for feed efficiency or residual feed intake) may produce less enteric CH_4 (Basarab et al., 2013; de Haas et al., 2017; Dini et al., 2019; Hegarty et al., 2007; Nkrumah et al., 2006; Pickering et al., 2015). However, Freetly et al. (2015) reported that cattle with greater feed efficiency actually produced more CH_4, thus raising some questions about the genetic factors associated with feed efficiency and CH_4 emissions. It is unclear whether the changes observed are a result of altered feed intake, ruminal microbial population, or rate of passage of feed through the digestive tract (Hammond et al., 2014; Johnson and Johnson, 1995). Additionally, recent information indicates that diet quality and feed efficiency interact to affect enteric CH_4 emissions: efficient cows produce less CH_4 when grazing high-quality pasture but not when grazing poor-quality forage (Jones et al., 2011). Residual feed intake is moderately heritable (0.28 to 0.58; Moore et al., 2009), so it might be possible to genetically select for animals with lower enteric CH_4 production. However, Donoghue et al. (2016) and Herd et al. (2014) suggested that selection for lower enteric CH_4 emissions might have negative effects on animal productivity. Simulations using published data indicate that without accurate feed intake information and a method by which many animals can be screened for CH_4 emissions, selection for lower enteric CH_4 emissions is not likely to be economically viable (Cottle et al., 2011).

Measurement of enteric CH_4 emissions from grazing cattle has been conducted primarily with animals grazing improved pastures using micrometeorological methods, tracer techniques, and automated head chamber systems (i.e., GreenFeed). Lassey (2007) summarized much of the CH_4 emissions data that had been collected using the SF_6 tracer technique and external markers to estimate forage intake. Estimated forage digestibility (in vitro) ranged from 49 to 83 percent, which resulted in estimated Y_m (i.e., enteric CH_4 as a percentage of GEI) ranging from 3.7 to 9.5 percent. The mean Y_m from all the studies was 6.25 percent, which agrees with the Y_m IPCC (2006, 2019) used for cattle on pasture. CH_4 emissions from cows grazing improved pasture, Kentucky fescue, and bermuda grass in the southern United States were reported by Pavao-Zuckerman et al. (1999) and DeRamus et al. (2003). In both studies, significant reductions in enteric CH_4 emissions per unit of animal BW gain resulted from the implementation of best management practices designed to improve pasture quality. Pavao-Zuckerman at al. (1999) did not specify these pasture practices, but DeRamus et al. (2003) evaluated intensive grazing.

Enteric CH_4 emissions can be estimated using micrometeorological methods and tracer techniques. Todd et al. (2019) measured CH_4 emissions from beef cows grazing native Oklahoma range in October and May and reported a large variation in enteric emissions. In October, when cows were losing BW, they produced 87 g CH_4/head daily, and on the same pasture in May they produced 252 g CH_4/head daily (Olson et al., 2000). Westberg et al. (2001) measured CH_4 emissions from cows grazing the same pasture across seasons and found similar results, with higher CH_4 emissions from cows grazing lush spring growth and the lowest emissions from grazing stockpiled fall pasture. These differences are attributable to differences in both DMI and forage quality.

Stockers

Enteric CH_4 emissions of stocker cattle, while grazing, have been measured by Laubach et al. (2008), Tomkins et al. (2011), McGinn et al. (2011), Boadi et al. (2002), Gunter and Bradford (2017), and Gunter et al. (2017) using a variety of techniques including the SF_6 tracer, micrometeorological, and automated head chamber approaches. The same factors that affect CH_4 emissions from grazing beef cows are important in stocker cattle. Those factors are level of forage intake, digestibility of forage consumed, supplementation, and chemical composition of the plants consumed. Critical variables include estimations of feed intake and feed quality (chemical composition). However, many of the equations currently available may not accurately predict measured enteric CH_4 emissions from grazing cattle (Tomkins et al., 2011) or cattle fed harvested forages (Cole et al., 2020a).

Feedlot Cattle

Most estimates of enteric CH_4 emissions from finishing beef cattle are based on work using animals confined to respiration chambers, although a few studies have used micrometeorological methods in open feedlots or automated head chambers. Enteric CH_4 losses from finishing beef cattle normally range from 50 to 200 L/head/day (Beauchemin et al., 2008; Hales et al., 2012, 2013, 2014, 2015a, 2015b, 2017a, 2017b; Johnson and Johnson, 1995; Loh et al., 2008; McGinn et al., 2004; Todd et al., 2014a, 2014b). In most studies in the United States, diets have been based on dry-rolled or steamed-flaked corn, whereas in most studies in Canada the diets are based on barley. The IPCC Tier 2 (2006, 2019) enteric CH_4 conversion factor (Y_m) is 3 ± 1 percent of GEI for feedlot cattle fed steam-flaked corn-based diets and 3.9 percent of GEI for cattle fed barley diets. The primary factors that control enteric CH_4 emissions in feedlot cattle are feed intake, grain type, grain processing method, dietary roughage concentration and characteristics, feeding of an ionophore, and dietary fat concentration.

4-A.6.4 Factors Affecting Enteric Methane Emissions of Ruminants

Several factors may influence enteric fermentation and resulting CH_4 emissions. A thorough review of such factors is outside the scope of this document, but key factors have been reviewed by others (Beauchemin et al., 2008, 2020; Eckard et al., 2010; Hristov et al., 2013a, 2013b; Martin et al. 2010; Monteny et al., 2006; NASEM, 2016; Thompson and Rowntree, 2020) and are discussed briefly below or in other sections of this appendix. Many factors affect enteric CH_4 emissions, but the most critical factors are the:

- Level of dry matter intake
- Composition of the diet
- Digestibility of the organic matter

Benchaar et al. (2001) used the rumen digestion model of Dijkstra et al. (1992), as modified by Benchaar et al. (1998), and the CH_4 prediction system of Baldwin (1995) to estimate the effects of dietary modifications on the enteric CH_4 production of a 500-kilogram dairy cow. The model predicted enteric CH_4 production based on a ruminal hydrogen balance. Inputs into the model included daily DMI; chemical composition of the diet; solubility and degradability of protein and starch; degradation rates of protein, starch, and NDF; ruminal volume; and fractional passage rates of solids and liquid fractions from the rumen. Values modified in the simulations were DMI, dietary forage, concentrate ratio, starch availability (barley vs. corn), stage of maturity of forage, form of forage (hay or silage), particle size of alfalfa, and ammonization of cereal straw. The modeled effects of dietary changes on enteric CH_4 emissions in diets fed to dairy cows are presented in table 4A-2.

Table 4A-2. Summary of Effects of Various Dietary Strategies on Enteric CH_4 Production in

Strategy	CH_4 Variation (per Unit of GEI)	CH_4 Variation (per Unit of DE)
Increasing DMI	-9 to -23%	-7 to -17%
Increasing concentrate proportion in the diet	-31%	-40%
Switching from fibrous concentrate to starchy concentrate	-24%	-22%
Increased forage maturity	+15%	-15%
Alfalfa vs. timothy hay	+28%	-21%
Method of forage preservation (ensiled vs. dried)	-32%	-28%
Increased forage processing (smaller particle size)	-21%	-13%
Ammoniated treatment of poor-quality forage (straw)[a]	× 5	× 2
Protein supplementation of poor-quality forage (straw)	× 3	× 1.5

Source: Benchaar et al., 2001, table 12.

[a] Effects are due to significant increase in hay digestibility with no change in DMI.

4-A.6.5 Dietary Management Practices

Mitigating Enteric Methane in Dairy Cattle

Practices for mitigating enteric CH_4 production (g/day/cow) from lactating dairy cows in the United States include the incorporation of dietary management practices. These may include 3-nitrooxypropanol (3-NOP), nitrate, lipid supplementation, oilseeds, and tanniferous forages, and red algae (Arndt et al., 2020).

3-NOP

The inhibitor 3-NOP is an analog of methyl-coenzyme M that reacts with the nickel ion in the active site of methyl-coenzyme M reductase, thus competitively inhibiting the last step of the methanogenesis pathway in the rumen (Duin et al., 2016). The molecule is highly specific to methanogenesis and exhibits a positive dose-response behavior (Dijkstra et al., 2018; Melgar et al., 2020). The lowest effective dose recommended for dairy cows fed total mixed rations is 60 mg per kg of feed dry matter, without adverse effects on productivity. Dietary NDF content reduces the response in both dairy and beef cattle (Dijkstra et al., 2018). Higher 3-NOP doses may be needed for beef than for dairy cattle to achieve a similar reduction in CH_4 emissions (Dijkstra et al., 2018). The inhibitor 3-NOP is not yet registered for use in cattle in the United States but is expected to be registered in other countries soon. As of June 2023, Bovaer® (Elanco Animal Health Inc. and DSM-Firmenich) is available in 45+ countries, including the EU/EEA, Australia, Brazil, Chile, Pakistan, Switzerland, and Turkey, and has been the subject of multiple on-farm trials in 15+ countries and over 60 peer-reviewed studies (DSM, 2023).

Nitrate

Nitrate is a competitive hydrogen sink in the rumen, replacing carbon dioxide as the electron acceptor. Nitrate is reduced sequentially to nitrite and NH_3 following stoichiometric relationships (Honan et al., 2021). Nitrate supplementation reduces CH_4 production in a dose-dependent manner and elevated DMI decreases the effect of nitrate supplementation on CH_4 mitigation (Feng et al., 2020). Nitrate supplementation mitigates CH_4 production to a greater extent in dairy than in beef cattle. The greater mitigation efficacy in dairy cattle may be related to the use of slow-release nitrate only in beef cattle diets and to the generally greater feed intake in dairy. Nitrite is a toxic intermediate of nitrate reduction to NH_3 that can cause methemoglobinemia (Honan et al., 2021). Because of this, nitrates are recommended with caution and under supervisions of a trained or certified nutritionist. Nitrite toxicity in cattle can be prevented by controlling nitrate intake and gradual acclimation to higher doses but represents a health risk to the animals and can lead to death. Other toxicity prevention options such as encapsulation (slow release) and feeding denitrifying probiotics need more evidence for wide application.

Lipid Supplementation and Oilseeds

Dietary supplementation with lipids (oils and fats) modifies the rumen environment in several ways reducing enteric CH_4 production (Honan et al., 2021).

- Supplemental lipids replace fermentable carbohydrates, reduce the abundance and activity of protozoa and methanogens, provide an alternative hydrogen sink, and reduces fiber digestion shifting the ruminal metabolism to propionate production.
- Supplemental lipids also reduce DMI without affecting milk production and composition in some instances but reducing them in others (Hristov et al., 2013a). The general recommendation to prevent undesirable suppression of DMI is for total lipids, measured as ether extract, not to exceed 6–7 percent of diet dry matter. This maximum inclusion level limits the practical application of supplemental oils and fats to reduce CH_4 emissions in diets that contain ether extract below 6 percent of dry matter.
- Supplemental lipids reduce CH_4 in a dose-response manner. However, the response varies over a wide range depending on the fatty acid profile of the supplement and diet composition. Medium-chain and polyunsaturated fatty acids reduce CH_4 production most effectively (Honan et al., 2021) but feeding unsaturated fatty acids also increases the likelihood of milk fat depression mediated by the biohydrogenation intermediate trans-10, cis-12 conjugated linoleic acid (Palmquist and Jenkins, 2017).

- Feeding intact or extruded oilseeds is another practical way to increase the dietary lipid content to reduce CH_4 emissions.

Tanniferous Forages

Many browse and warm climate forages accumulate tannins. Tannins mitigate enteric CH_4 through mechanisms that are not well understood (Honan et al., 2021). Some evidence points to tannins reducing fiber digestion and hydrogen formation, and directly inhibiting methanogens. Tannins also have antiparasitic properties and antinutritional effects. The latter are more pronounced when dietary protein is limited because tannins reduce amino acid absorption (Hristov et al., 2013a), and high tannin doses can lead to intoxication. Tannins reduce CH_4 emissions in a linear dose-response manner, but the response is variable and reliable effects are only expected with tannin inclusion above 20 g/kg of diet DM (Jayanegara et al., 2011). Tanniferous forages, especially direct grazing of Lesdepeza species, can mitigate enteric CH_4 production (g/day) by 11.6 percent on average (Arndt et al., 2020). The recommendation to feed tanniferous forages only when grazing and exclude dietary tanning supplementation is based on the lack of a clearly understood mode of action, poor characterization of supplemental tannins, high variable response, and narrow dose range between CH_4 mitigation and risk for detrimental effects on animal nutrition and health.

Red Algae

The interest in macroalgae for mitigation of enteric CH_4 emissions in ruminants has dramatically increased in recent years, since Li et al. (2018) documented a strong anti-methanogenic effect of the red alga *Asparagopsis taxiformis* in sheep. Research groups around the globe have screened red, brown, and green macroalgae for anti-methanogenic effect (Dubois et al., 2013; Machado et al., 2014; Maia et al., 2016; Wasson et al., 2021) and while some species have shown promising results, *Asparagopsis* spp. (*taxiformis* and *armata*) appear to be the only ones with confirmed mitigating effect in in vivo experiments with dairy and beef cattle (Li et al., 2018; Roque et al., 2019; Kinley et al., 2020; Stefenoni et al., 2021).

The current understanding is that the anti-methanogenic activity of *Asparagopsis* spp. is based on its content of low molecular weight halogenated compounds, of which the brominated halomethane bromoform is dominant (Genovese et al., 2012). *Asparagopsis* spp. cause dramatic decrease in CH_4 emissions in vivo, but DMI may also decrease (Stefenoni et al., 2021) and there are concerns with the environmental impact of bromoform (ozone layer depletion) and effects on animal health and milk quality (Stefenoni et al., 2021; Muizelaar et al., 2021; Hegarty et al., 2021). Bromoforms are volatile and activity may decrease over prolonged storage, or if exposed to sunlight or heat (Stefenoni et al., 2021). Decreasing bromoform concentration and its intake will linearly diminish the mitigation potential of *A. taxiformis*. Based on data from Stefenoni et al. (2021) and unpublished data from Hristov et al. (n.d.), CH_4 yield will decrease by 1.5 to 2.0 g/kg DMI for every 100 mg/d increase in bromoform intake.

Long-term effects on animal productivity, health, reproduction, and milk quality need to be studied and the economics of mass application in the global dairy and beef industries are unclear. As a result of these uncertainties, Hegarty et al. (2021) rated the confidence in *Asparagopsis* spp. efficacy as “Low Agreement and Limited Evidence”. Research in this novel field will certainly continue in the near future, but its long-term impact on livestock GHG emissions is difficult to predict.

Mitigating Enteric Methane in Beef Cattle

Dietary Fat

Many studies have shown that supplemental fat can decrease enteric CH_4 emissions in ruminants. In a review of studies, Beauchemin et al. (2007) and Martin et al. (2010) noted that enteric CH_4

emissions (g/kg DMI) decreased by approximately 3.8 to 5.6 percent for each 1 percent increase in fat added to the diet. Similar decreases have been noted in sheep (Wang et al., 2018). Although added fat may reduce enteric CH_4 emissions, ruminants have a low tolerance for added dietary fat because it interferes with fiber digestion (Beck et al., 2019; NASEM, 2016). Thus, total fat level in the diet must usually be kept below 6–8 percent of dietary dry matter.

Grain Source, Grain Processing, Starch Availability

Grain source and grain processing method can also affect enteric CH_4 losses. In general, the greater the ruminal starch digestibility, the lower the enteric CH_4 emissions. At constant energy intake (two times maintenance), Hales et al. (2012) reported approximately 20 percent lower (2.5 vs. 3.0 percent of GEI) enteric CH_4 emissions in cattle fed typical high-concentrate (75 percent corn) steam-flaked-corn based finishing diets than in steers fed dry-rolled-corn-based diets. Similar responses were noted with the feeding of high-moisture corn compared with dry-rolled corn (Archibeque et al., 2006). Beauchemin and McGinn (2005) reported that enteric CH_4 emissions were 38 percent (barley) to 65 percent (corn) lower on high-concentrate (9 percent silage) finishing diets than on grower (70 percent silage) diets.

Feeding Coproduct Ingredients

Distillers grains with solubles (DGS) and other coproducts of the milling and ethanol industries are widely used as animal feeds. The effects of feeding 30 to 35 percent DGS (dry matter basis) in beef cattle feedlot diets on enteric CH_4 emissions have been variable, ranging from a significant decrease of 25 to 30 percent (McGinn et al., 2009) to no effect (Hales et al., 2012), and an increase (Hales et al., 2013). These differing results were probably due to differences in forage sources and processing and dietary fat characteristics. Researchers have reported conflicting results on the effect of DGS on nitrogen excretion, with some reporting a linear increase in N excretion with an increase of DGS inclusion in the diet (Hales et al., 2013). Some researchers note that the effect of DGS on nitrogen excretion are not known (Hünerberg, et al., 2013a; Hünerberg, et al., 2013b; Hünerberg, et al., 2014). Increased nitrogen excretion could lead to increased overall GHG emissions, even if CH_4 emissions may be reduced. Other research indicates the otherwise fate of coproducts not fed to animals should be considered, as the avoided emissions from landfills or composting could be considerable (de Ondarza and Tricarico, 2021). More research may be needed to fully understand the potential for emissions reductions.

Roughage Concentration and Form

The concentration and form of roughage in the diet will affect both enteric and manure CH_4 production (Beauchemin and McGinn, 2005; Hales et al., 2014). In general, as the concentration of forage in the diet increases, enteric CH_4 production increases and the quantity of volatile solids excreted increases. Using a ruminal volatile fatty acids stoichiometry model, Dijkstra et al. (2007) suggested that CH_4 losses from carbohydrate substrates (g/kg substrate) in a concentrate diet with a ruminal pH of 6.5 were 2.11, 3.18, 3.38, and 3.10 for starch, soluble sugars, hemicellulose, and cellulose, respectively. Similarly, with dairy cows, Moe and Tyrrell (1979) reported that enteric CH_4 production per unit carbohydrate digested was three times greater for cellulose than for hemicellulose. Aguerre et al. (2011) found that lactating dairy cattle emitted more CH_4 when the forage:concentrate ratio was changed from 47:53 to 68:32—0.54 kg CH_4/day vs. 0.65 kg CH_4/day, respectively. Blaxter and Wainman (1964) compared the effects of feeding diets with six hay to flaked corn ratios (100:0, 80:20, 60:40, 40:60, 20:80, 5:95) on enteric CH_4 emissions when fed at twice the maintenance level of intake. CH_4 emissions as a percentage of GEI increased slightly between the 100:0 diet (7.44 percent) and the 60:40 diet (8.17 percent), then decreased with the 5:95 diet (3.4 percent). In Ireland, Lovett et al. (2003) reported total daily enteric CH_4 emissions of 0.15, 0.19, and 0.12 kg/head (reported as 207, 270, and 170 L/head) for heifers fed diets containing

65, 40, and 10 percent forage (the remainder as concentrate), respectively. As a percentage of GEI, losses were 6.1, 6.6, and 4.4 percent, respectively.

Roughage Quality

Using steers fed all-forage diets, Ominski et al. (2006) reported that, within the range of forage qualities tested (alfalfa-grass silage containing 61, 53, 51, or 46 percent NDF, dry matter basis), enteric CH_4 emissions of steers, as a percentage of GEI, were not significantly affected by NDF content (5.1 to 5.9 percent), although daily CH_4 production tended to be highest for the 53 percent NDF diet (0.12, 0.15, 0.13, and 0.14 kg/head/day, respectively). Similarly, using grazing sheep, Milano and Clark (2008) reported no effect of forage quality (perennial rye grass—52 or 47 percent NDF, 77 or 67 percent organic matter digestibility) on enteric CH_4 emissions. Cole et al. (2020a) noted that daily enteric CH_4 emissions were not affected by forage quality in steers fed a low-quality grass hay in combination with alfalfa hay. However, CH_4 emissions per unit of organic matter digested decreased linearly as forage quality increased. Protein supplementation of the low-quality forage did not affect total CH_4 emissions but decreased CH_4 per kg digestible organic matter.

Although, in some instances, there may be limited effect of forage quality on enteric CH_4 emissions, forage quality will affect digestibility and excretions of VS in feces, thus affecting CH_4 emissions from manure. Therefore, feeding more easily digestible forages or concentrates may decrease VS excretion thereby decreasing CH_4 emissions from manure (Boadi et al., 2004; Ominski et al., 2006; Cole et al., 2020a).

Level of Feed Intake

Blaxter and Wainman (1964) noted that enteric CH_4 emissions, as a percent of GEI, were 23 percent greater in steers fed at maintenance than in steers fed at twice maintenance (8.1 vs. 6.6 percent of GEI, respectively). However, in a study evaluating emissions from cattle fed ryegrass diets, Milano and Clark (2008) reported that as DMI increased from 0.75 percent of maintenance to two times maintenance, enteric CH_4 emissions (g/day) increased linearly (r^2 = 0.80 to 0.84). Emissions as a percentage of GEI were not affected by DMI and ranged from 4.9 to 9.5 percent of GEI (15.9 to 30.4 g/kg DMI).

Using a high-forage (70 percent barley silage) or medium-forage (30 percent silage) diet fed at levels from maintenance to about 1.8 times maintenance, Beauchemin and McGinn (2006b) noted that enteric CH_4 emissions, as a percent of GEI, decreased by approximately 0.77 percentage units[1] for each unit increase in feed intake (expressed as level of feed intake above maintenance). This was less than the estimate using the Blaxter and Clapperton (1965) equation (0.93 to 1.28 percentage units) or the 1.6 percentage units suggested by Johnson and Johnson (1995).

Feed Additives and Growth Promoters

Cooprider et al. (2011) noted that the daily CH_4 and manure N_2O emissions by beef cattle fed through a "natural" program with no use of antibiotics, ionophores, or growth promoters were similar to those from beef cattle fed in more traditional systems that used anabolic implants and diets that contained ionophores and beta-agonists. However, typical beef cattle had greater average daily BW gains (1.85 vs. 1.35 kg/day) and thus took 42 fewer days to reach the same end point (596 kg BW). Hence, beef cattle fed using modern growth technologies had 31 percent lower GHG

[1] This appendix uses the term "percentage units" to refer to changes in diets or emissions that are *not* proportional to their baselines. For example, a reduction in emissions from 3 percent to 1 percent is a two "percentage unit" reduction, or a *67-percent reduction*.

emissions per head. CH_4 emissions per kilogram of BW gain was 1.1 kilogram greater for the "natural" cattle (5.02 vs. 3.92 CO_2-eq/kg BW gain) than the traditional beef cattle.

Odongo et al. (2007) reported that monensin (24 ppm) in dairy diets decreased enteric CH_4 by 7 to 9 percent for up to 6 months, while Waghorn et al. (2008) reported no effect of monensin delivered by controlled-release capsules in dairy cows grazing pasture, and Hamilton et al. (2010) also found no change in enteric CH_4 production from monensin when fed to dairy cows offered a total mixed ration.

A number of studies have shown that a variety of halogenated analogues have the potential to dramatically decrease ruminal CH_4 production (Cole and McCroskey, 1975; Johnson, 1972, 1974; Tomkins and Hunter, 2004; Tomkins et al., 2009; Trei et al., 1972). In general, the effect was greater in cattle fed high-forage diets than in cattle fed high-concentrate diets. When CH_4 emissions were dramatically reduced, a significant quantity of hydrogen could be lost (1 to 2 percent of GEI) via eructation, suggesting an alternative electron sink is also needed. In general, the compounds did not improve production efficiency significantly. In addition, the potential toxicity of these compounds made them impractical for routine use where formulation errors in the field are possible.

A number of studies have demonstrated that feeding nitrates in place of urea in cattle diets can significantly decrease enteric CH_4 production (Dijkstra et al., 2018; Feng et al., 2020; Honan et al., 2021; Lee et al., 2015, 2017a, 2017b; Velazco et al., 2014). However, the risk of nitrate toxicity may limit the use of this technology in real practice.

Several studies have suggested that feeding of condensed tannins can decrease enteric CH_4 production by 13 to 16 percent, either through a direct toxic effect on ruminal methanogens or indirectly via a decrease in feed intake and diet digestibility (Arndt et al., 2020; Eckard et al., 2010; Min et al., 2020; Moraes et al., 2014, 2018; Niu et al., 2018). Tannins may also shift nitrogen excretion away from urine to feces and inhibit urease activity in feces, which could decrease NH_3 and N_2O emissions from manure (Powell et al., 2009, 2011). In arid environments, nearly all urinary nitrogen is volatized (Russelle, 1992), so if dietary tannin supplementation could shift nitrogen excretion from urine to feces less may be volatized into the atmosphere.

Feeding yeast cultures, enzymes, dicarboxylic acids (fumarate, malate, acrylate), and plant secondary compounds, such as saponins, may decrease enteric CH_4 emissions under some feeding conditions (Beauchemin et al., 2008; Beauchemin and McGinn, 2006a; Eckard et al., 2010; Martin et al., 2010; McGinn et al., 2004; Ungerfeld et al., 2007).

Novel Microorganisms and Their Products

Klieve and Hegarty (1999) noted that enteric CH_4 emissions may be biocontrolled directly by use of viruses and bacteriocins. Lee et al. (2002) reported that a bacteriocin (Bovicin HC5) from *Streptococcus bovis* reduced in vitro CH_4 production by up to 50 percent. It appeared, that in contrast to results with monensin, the ruminal microorganisms did not adapt to the bacteriocin. Further, Australian researchers have suggested that vaccinating against methanogens can decrease CH_4 emissions. However, the results have not been consistent (Eckard et al., 2010; Wright et al., 2004) because efficacy is dependent on the specific methanogen population and that is dependent on diet, location, and other factors.

Genetics

Potential genetic effects are discussed in section 4-A.5.2.

4-A.7 Background on Housing Emissions

Emissions from animal housing are highly dependent upon the type of housing (pasture, open lot, confinement, etc.), bedding used, and animal species. For example, CH_4 emissions from beef or dairy dry lot operations seems to be low, whereas emissions of N_2O can be significant. Examples of reported emissions from varying dairy cattle housing systems are presented in table 4A-3.

Table 4A-3. Examples of Reported On-Farm Emissions Estimates for CH_4, N_2O, and NH_3 From a Variety of Dairy Cattle Housing Systems

Housing	Country	Emissions (g/Cow/Day)			Reference
		CH_4	N_2O	*NH_3*	
Barn	Germany	402		*64.8*	Saha et al. (2014)
Tie stall barn	Austria	170–232[a]	0.14–1.2[a]	*4–7.4*[a]	Amon et al. (2001)
Barn	Germany	256	1.8	*14.4*	Jungbluth et al. (2001)
Dry lot	United States			*41–140*	Cassel et al. (2005)
Hardstanding	United Kingdom	0.03[b]	0.01	*11*	Ellis et al. (2001)
Open-freestall	United States	410	22	*80*	Leytem et al. (2013)
Tie stall barn	Canada	390			Kinsman et al. (1995)
Pasture	New Zealand	300–427			Laubach and Kelliher (2005)
Dry lot	United States	490	10	*130*	Leytem et al. (2011)
Standoff pad	New Zealand	1.66[b]	0.03		Luo and Saggar (2008)
Barn	Denmark	256	1.2	*16*	Zhang et al. (2005)
Dry lot	China	397	37		Zhu et al. (2014)
Barn	Sweden	216–312[a]		*21–27*[a]	Ngwabie et al. (2009)
Barn	Germany	464	45	*92.4*	Samer et al. (2011)
Pasture	Uruguay	372			Dini et al. (2012)

[a] Measured in g/LU/day, where an LU (livestock unit) = 500 kg.

[b] Measurements do not include enteric CH_4 production.

Variations in emissions from housing are due to factors such as temperature, diet composition, water consumption, ventilation flow rates, type of manure handling systems, manure removal frequency, feces and urine characteristics (i.e., pH, VS and total ammoniacal nitrogen), and type of bedding used. Although differences can be great between emission rates, there are some emission characteristics that are consistent across most studies.

Many studies have reported strong diel trends in emissions of CH_4 and NH_3, with emissions tending to be lower in the late evening and early morning and then higher throughout the day until early evening (Aguerre et al., 2011; Amon et al., 2001; Bjorneberg et al., 2009; Cassel et al., 2005; Flesch et al., 2009; Hales and Cole, 2017; Leytem et al., 2011; Ngwabie et al., 2009; Powell et al., 2008; Sun et al., 2008; Todd et al., 2011a, 2014a, 2015). This strong diel trend in emissions can be associated with wind speed and temperature, as winds tend to be light in the late evening and early morning and then, in most instances, steadily increase throughout the day to reach a peak in the late afternoon. Temperature also increases from early morning to late afternoon, and then decreases again. Additionally, animal activity tends to increase from morning to late afternoon as animals wake and begin to eat, drink, ruminate, defecate, and urinate. As these activities increase, one would expect an increase in CH_4 (and NH_3) emissions.

There are also seasonal trends in emissions, the most prominent being in NH_3 emissions, with the lowest rates in winter compared with the other seasons (Aguerre et al., 2011; Amon et al., 2001; Bjorneberg et al., 2009; Flesch et al., 2009; Leytem et al., 2011; Powell et al., 2008; Todd et al., 2011a). Powell et al. (2008), Flesch et al. (2009), and Aguerre et al. (2011) reported that dairy barn emissions of NH_3 in Wisconsin were lowest in winter, with winter rates about one-half to one-third lower than those in the spring and summer, which was attributed to cold winter temperatures. In general, N_2O emissions from housing were found to be low and showed no discernible diel or seasonal trends (Adviento-Borbe et al., 2010; Bjorneberg et al., 2009; Leytem et al., 2011; Ngwabie et al., 2009). There are consistent reports of both diel and seasonal variations in both CH_4 and NH_3 emissions, so it is imperative that these factors be captured in any estimation of emissions for a given production system.

Amon et al. (2001) examined CH_4 emissions from a tie-stall dairy barn in Austria using either a slurry-based system or a straw-based system. In both systems, about 80 percent of the net CH_4 emissions were due to enteric fermentation, with the remaining amount coming from the manure. Sun et al. (2008) measured CH_4 emissions from dairy cows and fresh manure in chambers and reported that fresh manure alone did not produce noticeable CH_4 fluxes. In some dairy production systems, manure is removed from the animal housing area often; therefore, CH_4 emissions from animal housing areas of a dairy can be largely attributed to enteric emissions. When manure is stored mainly as a liquid, however, manure CH_4 emissions may exceed enteric emissions (Arndt et al., 2018 Todd et al., 2011b). N_2O emissions tend to be negligible from both animals and fresh manure. The majority of N_2O emissions result from manure storage, pasture, and land application of manures. Therefore, the main sources of N_2O emissions from animal housing would be dry lots, feedlots, and stand-off pads, because there is potential for deposited nitrogen to be nitrified and denitrified under wet conditions and lost as N_2O. Luo and Saggar (2008) measured N_2O and CH_4 emissions from a dairy farm stand-off pad in New Zealand and reported N_2O fluxes from 0 to 3 g N_2O-N/day, which they attributed to the concentrations of water and nitrate in the pad materials. Overall, only 54 g of N_2O-N was emitted from the pad over the time of use, representing ~0.01 percent of the excreta nitrogen deposited on the pad.

In nonruminant systems, GHG emissions are dominated by housing and manure handling, as there is very little enteric CH_4 and N_2O production. Liu et al. (2013) conducted a meta-analysis to identify factors that contribute to GHG emissions from swine production. Findings, shown in table 4A-4, illustrate that type of emission source (swine buildings or manure storage facilities) was not significant for CH_4 and N_2O emissions. Liu et al. (2013) found that:

- Swine buildings with straw-flow systems generated the lowest CH_4 and N_2O emissions of systems compared, while pit systems generated the highest CH_4 emissions and bedding systems generated the highest N_2O emissions.
- Emissions from lagoons and slurry storage basin/tanks were compared; lagoons generated significantly higher N_2O emissions than slurry storage basin/tanks, while CH_4 emissions were not different.
- Straw-based bedding resulted in numerically higher CH_4 but lower N_2O emissions when compared with sawdust or corn stalk bedding systems.
- There is an increasing trend for CH_4 emissions as manure removal frequency decreased ($P = 0.13$).

- Deep pits and pits flushed using lagoon effluent also generated relatively high CH_4 emissions.
- Results for N_2O emissions showed very high uncertainties (P = 0.49).
- Deep pits and pits with manure removed every 3 or 4 months had relatively higher N_2O emissions.
- CH_4 emissions from slurry storage facilities without covers were significantly higher than from those with covers.
- When evaluating stage of production, the highest CH_4 emissions were from farrowing swine and were significantly higher than those from finishing and nursery swine. Compared with farrowing swine, the gestating swine had significantly lower CH_4 emissions.

The highest N_2O emissions were from gestating swine and were significantly higher than those from finishing swine.

Table 4A-4. P Values of Main Effects on GHG Emissions From Swine Operations

Cause of Variation	CH_4 (n=76)	N_2O (n=53)
Emission source	0.94	0.93
Swine category	0.05	<0.01
Geographic region	0.04	0.02
Temperature	0.20	0.95
Size of operation	0.89	0.24

Source: Liu et al. (2013).

Greenhouse gas emissions from broiler chicken production will originate almost exclusively from the animal housing, which also serves as the storage location for manure. Liu et al. (2011) reported that for a 20-week grow-out of turkeys on litter, average daily N_2O emissions were 0.045 g/kg bodyweight and daily CH_4 emissions were 0.08 g/kg bodyweight. If a house is cleaned or decaked (removal of the top, crusted portion of the litter) and stored on the farm, GHG and NH_3 production and emissions could occur. Practices to decake and the timing of land application of cake and litter vary from site to site and may or may not include further composting.

Greenhouse gas emissions from egg production will originate from the housing or the manure storage location. Laying hen housing systems without litter would likely exhibit greater emissions than litter systems, but comparisons of estimates are sparse. Laying hen houses typically store excreta in a basement or may move excreta out of the house frequently (daily or more often); this would relocate emissions to a storage shed rather than change the cumulative emissions unless some form of processing (drying) took place prior to storage. Li et al. (2010) reported daily CH_4 emissions of 39.3 to 45.4 mg/hen and N_2O emissions of 58.6 mg/hen (hen bodyweight average = 1.9 kg) in a basement-type system. This compares to a litter system for a 20-week grow-out of turkeys where average daily N_2O emissions were 0.045 g/kg bodyweight and daily CH_4 emissions were 0.08 g/kg bodyweight (Liu et al., 2011). Based on the comparison of these two studies, differences in GHG emissions from dry litter systems and wetter, stacked laying hen systems would be expected.

4-A.8 Background on Manure Management Emissions

Manure storage and treatment, as a component of manure management systems, plays a critical role in GHG emissions and their mitigation. At the entity level, various manure storage and treatment approaches will lead to different amounts of GHG emissions. Animal manure can be classified into two categories based on their physical properties: solid (more than 15 percent dry matter) and liquid (less than 15 percent dry matter, including liquid manure with less than 10 percent dry matter and slurry manure with 10–15 percent dry matter).

At the farm entity level, several practices are often strategically combined to treat manure. Activity data (i.e., mass flow data and chemical and physical characteristics of influent and effluent, environmental temperature, pH, and total nitrogen) from individual practices can be used to link practices in the combined system for individual farm entities.

In general, CH_4 emissions from manure management will vary depending on the amount of volatile solids stored, the maximum CH_4 generation potential of those solids, moisture content (aerobic vs. anaerobic environment), temperature, and length of storage. N_2O emissions from manure management will be affected by the total nitrogen content of the manure, use of bedding, loss of nitrogen as NH_3, moisture content (aerobic vs. anaerobic environment), temperature and length of storage. Therefore, both the animal category and manure handling and storage system will have large impacts on the total GHG emissions.

4-A.8.1 Temporary Stack and Long-Term Stockpile

Management methods for stored manure are differentiated by the length of time they are stockpiled:

- Temporary stack is a short-term manure storage method that is used to temporarily hold solid manure when bad weather prohibits land application, and/or when there is limited availability of cropland for manure application. With temporary stack, the manure is removed and applied to land within a few weeks of piling. Temporary storage is not a preferred method to store manure because it requires the manure to be handled twice.
- Long-term storage is a method in which solid manure is piled on a confined area or stored in a deep pit for longer than 6 months. In low-rainfall areas, the stockpile can be piled on the field with the installation of nutrient runoff control. In higher rainfall areas, a concrete pad and wall are constructed to store solid manure and prevent nutrient runoff from heavy rain.

Carbon and nitrogen compounds in manure are broken down by microbes to CH_4, and N_2O. The main factors influencing GHG emissions from storage are temperature and storage time. Due to the longer storage time, long-term stockpile solid manure storage generates a significant amount of GHGs. Temporary stack, as a short-term manure storage method, generates less GHGs than the long-term stockpile solid storage. However, it is still necessary to quantitatively delineate the emissions to help animal farms evaluate their manure management operations.

4-A.8.2 Composting

Composting is the controlled aerobic decomposition of organic material into a stable, humus-like product (USDA, 2007). Animal manure may be composted in a variety of different systems, including in-vessel systems, windrows, or static piles. In-vessel systems are closed—for example, a rotary drum or box that uses regular movement to ensure proper aeration. The largest composting operations divide up the compost into long heaps for windrow composting or into one large pile for aerated static pile composting. In the former method, proper oxygen flow can be maintained via manual turning or pipe systems; in the latter method, it is maintained through pipe systems. Composting has become a popular method in some regions to decrease the volume and weight of animal manure and to produce a product that is often more acceptable to farmers as a fertilizer. Furthermore, the heat generated through the composting process can kill parasites, pathogens, and weed seeds found in animal waste, creating a safer product for crop application.

The quantity of GHG emissions is affected by the composting method employed and manure characteristics (carbon, nitrogen, and carbon:nitrogen). To the extent that the rate of GHG formation depends on oxygen saturation in the pore space, aeration method (i.e., forced-air vs. passive/convective) and rate (or turning frequency) will affect the magnitude of GHG emissions during the composting process.

4-A.8.3 Aerobic Lagoons

Aerobic lagoons are artificial outdoor basins that hold animal wastes. The aerobic treatment of manure involves the biological oxidation of manure as a liquid, with either forced or natural aeration. Natural aeration is limited to aerobic lagoons with photosynthesis and is consequently shallow to allow for oxygen transfer and light penetration. These systems become anoxic during low-sunlight periods. Due to the depth limitation, naturally aerated aerobic lagoons have large surface area requirements and are impractical for large operations and subsequently there are few truly aerobic lagoons used for manure treatment.

4-A.8.4 Anaerobic Lagoons, Storage Basins, Runoff Holding Ponds, and Storage Tanks

The most frequently used liquid manure storage systems are anaerobic lagoons (in the southern United States), earthen or earth-lined storage basin (in the northern part of the country), runoff holding ponds, and above-grade storage tanks. Anaerobic lagoons are earthen basins that provide an environment for anaerobic digestion and storage of animal waste. Both the American Society of Agricultural and Biological Engineers and USDA’s Natural Resources Conservation Service have engineering design standards for construction and operation of anaerobic lagoons. Storage basins collect liquid manure from flush systems, milking parlors, holding areas, etc. with most being earthen basins not specifically designed for manure treatment as are anaerobic lagoons. In most feedlots, a holding pond is constructed to collect runoff for short-term storage. Storage tanks range from lower cost earthen basins to higher cost, glass-lined steel tanks. The manure that enters these systems is usually diluted with flush water, water wasted at stalls, and rainwater.

All of these storage systems (without aeration) are biologically anaerobic lagoons, which means that they have similar potential to produce CH_4 and N_2O. Due to the large quantity of liquid manure produced in the United States, liquid manure storage can be a major source of GHG emissions from animal operations. In terms of estimation of GHG emissions from anaerobic lagoon/runoff holding pond/storage tanks, these storage systems are classified into four categories:

- Covered storage with a crust formed on the surface
- Covered storage without a crust formed on the surface
- Uncovered storage with a crust formed on the surface
- Uncovered storage without a crust formed on the surface

4-A.8.5 Anaerobic Digester With Biogas Utilization

One of the most commonly discussed manure management alternatives for GHG reduction and energy generation is anaerobic digestion. Anaerobic digestion is a natural, biological conversion process that has been proven effective at converting wet organic materials into biogas (approximately 60 percent CH_4 and 40 percent CO_2). Biogas can be used as a fuel source for engine-generator sets, producing relatively clean electricity while also reducing some of the environmental concerns associated with manure. The digester can be as simple as a covered anaerobic lagoon (Gould-Wells and Williams, 2004) or as sophisticated as a thermophilic or media matrix (attached growth) digester (Cantrell et al., 2008). There are a wide variety of anaerobic digestion configurations, such as continuous stirred tank reactor (CSTR), covered lagoon, plug-flow, temperature phased, upflow anaerobic sludge blanket (UASB), packed-bed, and fixed film. The digestion is also categorized based on culture temperature: thermophilic digestion in which manure is fermented at a temperature of around 55 °C, or mesophilic digestion at a temperature of around 35 °C. Among these technologies, CSTR, plug-flow, and covered lagoon, all under mesophilic conditions, are the most often used methods.

During anaerobic digestion, a group of microbes work together to convert organic matter into CH_4, CO_2, and other simple molecules. The main advantages of applying anaerobic digestion to animal manures are odor reduction, electricity generation, and the reduction of GHG emissions and manure-borne pathogens. Anaerobic digestion is also an excellent pretreatment process for subsequent manure treatment to remove organic matter and concentrate phosphorus. Considering the small amount of N_2O existing in biogas, N_2O emissions are not estimated for the anaerobic digestion of liquid manure.

The challenges associated with anaerobic digestion relate to initial capital cost, operation, and maintenance and other gases that may be generated (e.g., nitric oxides). The economics relate to access to the electrical grid and sufficient green-electricity offsets to make the operation profitable. Profitable conditions are relatively scarce. Finally, the digester sludge must be managed. Another conversion alternative with energy creation potential is thermochemical conversion (Cantrell et al., 2008). Systems that use thermochemical conversions to syngases, bio-oil, and biochar for electricity and fuel are emerging, but are not yet established.

4-A.8.6 Solid–Liquid Separation

Solid–liquid manure separation has been used widely by dairy farms. One purpose of solid–liquid separation is to physically separate and remove the larger solids from liquid manure in order to store and treat them separately. The available commercial methods include gravity sedimentation and mechanical separation (with or without coagulation flocculation). Sedimentation and mechanical separation without coagulation flocculation are the most popular methods used by animal farms. GHG emissions from the operation are minimal; however, separation has an impact on nutrient distribution in separated solid and liquid manure, which will influence GHG emissions from the next stage of manure storage and treatment for solid and liquid manure. The separated liquid manure is treated as the influent for the next step of storage and treatment operations.

Appendix 4-B: Method Documentation

The following provides the rationale for the chosen method as well as any additional technical documentation not provided in the chapter. For the following documentation sections, uncertainty guidance may include a range. To assign an appropriate uncertainty to a given parameter consider that uncertainty depends on the availability of "reliable and representative survey data that differentiates animal populations by system usage" (IPCC, 2006). IPCC (2006) notes that "[a]ccurate and well-designed emission measurements from well [characterized] types of manure and manure management systems can help reduce these uncertainties further." Volume I, chapter 3 of IPCC (2006) describes how to elicit expert judgement on uncertainty.

4-B.1 Enteric Methane Emissions From Dairy Cattle

4-B.1.1 Rationale for Methods

There are many equations available in the scientific literature to estimate enteric CH_4 emissions from lactating dairy cows and nonlactating dairy cows and heifers. The methods selected here represent the most accurate empirical equations derived from recent meta-analyses of individual animal records (lactating cows) or published treatment means (nonlactating cows, heifers) in the United States. The most accurate equations for lactating cows, nonlactating (dry) cows, and heifers in these publications were selected by evaluating the root mean square prediction error (RMSPE) to assess prediction accuracy and other available model performance indicators to assess bias. The use of the empirical equations by Niu et al. (2018) and Moraes et al. (2014) is recommended over the IPCC Tier 2 equation (IPCC, 2019) to estimate enteric CH_4 emissions because they were derived with individual animal records from studies conducted in the United States.

4-B.1.2 Technical Documentation

Additional technical documentation and discussion of uncertainty for dairy cattle is provided below.

Uncertainties in the parameters for the lactating cows are given in equation 4B-1. USDA hopes to prioritize filling this gap in the next version of the report. Uncertainties in parameters for the nonlactating cows are given in equation 4-B-2, and for dairy heifers in equation 4B-3. The available information does not quantify all uncertainty associated with GEI used in the calculation for the nonlactating cows and dairy heifers.

Use the explicit model-based method to estimate uncertainty for dairy cattle enteric fermentation (see chapter 8). Uncertainty is assumed to be minor for the management activity data provided by the entity, and therefore the values are assumed to be certain. Uncertainties in parameters are propagated through the calculations using a Monte Carlo simulation. See chapter 8 for more information about the explicit model-based method.

Estimating Enteric Methane Emissions From Lactating Cows

Niu et al. (2018) developed various equations to estimate CH_4 emissions from enteric fermentation in lactating dairy cows using 1,084 individual dairy cow records from 45 studies conducted in the United States with primarily Holsteins (91 percent) and Jerseys (9 percent). The CH_4 emissions equation for lactating cows (Niu et al., 2018) contained the most prediction variables and had the highest prediction accuracy, as indicated by the lowest RMSPE.

Equation 4B-1: Quantifying Uncertainty for Enteric Fermentation CH_4 Emissions From Lactating Cows

$$CH_4 = -126 + 11.3 \times DMI + 2.30 \times NDF + 28.8 \times MF + 0.148 \times BW$$

Where:

Intercept	=	126
Parameter for *DMI*	=	11.3
Parameter for *NDF*	=	2.30
Parameter for *MF*	=	28.8
Parameter for BW	=	0.148

The explicit model-based method requires a covariance matrix for joint probability draws from the model parameters and intercept, along with the random effects for the Monte Carlo simulation. Use expert judgement or elicit expert judgement for uncertainties.

Estimating Enteric Methane Emissions From Nonlactating (Dry) Cows and Dairy Heifers

Moraes et al. (2014) developed CH_4 emissions prediction equations from individual animal records from 62 studies conducted in the United States as follows: 591 Holstein and Jersey nonlactating cow records, and 414 Holstein, Angus, Hereford, and Angus-Hereford cross heifers. The CH_4 emissions equations for nonlactating cows and heifers that had the lowest RMSPE and highest prediction accuracy were the simple models based on GEI.

Equation 4B-2: Quantifying Uncertainty for Enteric Fermentation CH_4 Emissions From Nonlactating Cows

$$CH_{4,MJ} = 2.381 + 0.053 \times GEI$$

Where:

Intercept	=	2.381
Parameter for *GEI*	=	0.053

The explicit model-based method requires the following standard deviations associated with the model parameter and intercept for the Monte Carlo simulation:

	Intercept
Intercept	0.153
GEI	0.001

Estimating Enteric Methane Mitigation by Feeding 3-NOP, Nitrate, and Lipid Supplementation in Dairy Cattle

The strategies for mitigating enteric CH_4 emissions from dairy cattle and the methods to calculate the magnitude of the reduction were selected based on the availability of meta-analyses that quantitatively evaluated explanatory variables that explain the heterogeneity quantitative effects and their variation in the CH_4 mitigation response for each mitigant (Dijkstra et al., 2018; Feng et al., 2020). Only the mitigants that reduced enteric CH_4 emissions significantly (more than a 10 percent reduction) without decreasing animal productivity are recommended.

Equation 4B-3: Quantifying Uncertainty for Enteric Fermentation CH_4 Emissions From Dairy Heifers

$$CH_{4,MJ} = 1.289 + 0.051 \times GEI$$

Where:

Intercept = 1.289

Parameter for *GEI* = 0.051

The explicit model-based method requires the following standard deviations associated with the model parameter and intercept for the Monte Carlo simulation:

	Intercept
Intercept	0.185
GEI	0.001

4-B.2 Enteric Methane Emissions From Beef Cattle

4-B.2.1 Rationale for Method

There are many equations available in the scientific literature to estimate enteric CH_4 emissions from beef cattle. The diets of beef cattle are highly variable, so the most appropriate method depends heavily on diet and cattle type (cows, replacement heifers, stockers, feedlot cattle).

The methods used for cows and stockers are those used by IPCC. This chapter presents a modified IPCC method for feedlot cattle, which is more representative than other available methods such as equations derived from recent meta-analyses of beef cattle studies in the United States and Canada. Most available equations do not have a correction for grain type or grain processing method, both of which have significant effects on enteric CH_4 production. Based on our evaluation, the model developed for feedlot cattle had the highest prediction accuracy as indicated by the lowest standard error of the estimate (S_{yx}) and greatest Lin's concordance coefficient.

The most recent Nutrient Requirements of Beef Cattle (NASEM, 2016) recommend the use of up to five empirical equations to estimate CH_4 emissions of feedlot cattle (IPCC, 2006; Ellis et al., 2007, 2009; Escobar et al., n.d.). Ellis et al. (2009) reported that several equations appeared to be good predictors of enteric CH_4 losses by feedlot cattle fed barley-based diets in Canada. However, many of those equations tend to greatly overestimate enteric CH_4 losses when compared with data from cattle fed more typical U.S.-style finishing diets based on corn (Hales et al., 2012, 2013; Todd et al., 2014a, 2014b). Kebreab et al. (2008) reported that MOLLY and IPCC Tier 2 (2006) gave predicted values similar to measured values with feedlot cattle, but there was a large variability in individual animals, with errors of 75 percent or greater. Kebreab et al. (2008) noted the average Y_m (MJ enteric CH_4/MJ GEI) for feedlot cattle based on experimental data was 3.88 percent (range 3.36 to 4.56), which was higher than the IPCC (2006) value of 3.0 percent and the values with typical Southern Great Plains finishing diets of 2.85 to 3.03 percent (Hales et al., 2012, 2013; Todd et al., 2014a; 2014b). The more recent IPCC guidance (IPCC, 2019) recommends a Y_m of 3.9 for feedlot diets based on dry-rolled corn or barley and 3.0 for diets based on steam-flaked corn. The purpose of the current model/decision tree was not to estimate CH_4 inventories, but to estimate the effects that changes in diet and management have on CH_4 emissions by cattle.

Calculating Gross Energy Requirements

The equations selected for estimating gross energy requirements and feed intake of grazing and feedlot cattle were chosen from those preferred in the NASEM (2016).

4-B.2.2 Technical Documentation

Uncertainty Discussion

The uncertainty of Tier 2 Y_m values for grazing and feedlot beef cattle reported by IPCC (2019) was ±20 percent. The uncertainty for total U.S. enteric fermentation emissions reported by the U.S. EPA (2020) was -11 to +18 percent.

The method presented for feedlot beef cattle enteric CH_4 emissions appears to be as accurate or more accurate than the equations proposed by NASEM (2016) or the IPCC (2019) Y_m values of 3.0 and 3.9 percent. If the uncertainty is calculated as the standard error divided by the mean, the uncertainty of these estimates would range from 30 to 45 percent. However, the proposed uncertainty of IPCC (2019) Y_m values is ±20 percent. Because the proposed model appears to be more representative of U.S. values than the IPCC (2019) Y_m values, the uncertainty of ±20 percent is recommended.

Model for Adjusted Feedlot Y_m

Currently, the IPCC (2019) Tier 2 model may be the easiest method for estimating CH_4 emissions from feedlot beef cattle. Unfortunately, the Tier 2 method does not allow for estimating changes in enteric CH_4 emissions related to changes in diet or management. A modified Tier 2 IPCC (2006, 2019) method is recommended to estimate enteric CH_4 emissions from beef cattle fed high concentrate finishing diets. The CH_4 conversion factor (Y_m) is adjusted by factors in the animals' diets as described in section 4.2.2.1. A baseline scenario, based on typical U.S. beef cattle feeding conditions, is established, and the Y_m values are adjusted based on published research. Emission values are modified using correction factors that are based on changes in animal management and feeding conditions from the baseline scenario.

We used a Y_m of 3 percent as the baseline value, as recommended by the IPCC (2006, 2019) estimates and supported by Todd et al. (2014a), who measured CH_4 emissions from a feedyard in the Texas Panhandle at which cattle were fed diets similar to the presented "baseline" scenario.

To evaluate the feedlot cattle Y_m adjustment model, a dataset consisting of 33 studies and 99 to 105 treatment means was developed. The authors evaluated the model by comparing the proposed model to models adjusted for baseline Y_m (2, 3, 3.5, or 4 percent of GEI), effect of fat supplementation (2, 4, or 6 percent per 1 percentage unit increase in dietary fat content), effect of steam flaking grain (10, 20, or 30 percent), dietary starch:NDF adjustment (0.30, 0.45, or 0.60 units), and monensin adjustment (0.12 or 0.30 percentage units). Predicted Y_m and daily enteric CH_4 production (g/day) were compared to actual values using linear regression with and without a Y intercept and Lin's concordance correlation (Lin, 1989). In general, the adjustments tested had only minor effects on r^2 and standard error of the estimate (S_{yx}).

The regressions of predicted vs. actual Y_m and predicted vs. actual CH_4 (g/day) are as follows:

$$\text{Predicted } Y_m = 3.41(\pm0.22) + 0.261(\pm0.049) \times \text{actual } Y_m \ (r^2 = 0.214, S_{yx} = 0.69)$$

$$\text{Predicted } Y_m = 0.972(\pm0.026) \times \text{actual } Y_m \ (r^2 = 0.928, S_{yx} = 1.24)$$

$$CH_4 \text{ (g/day)} = 18.49(\pm10.98) + 1.232(\pm0.097) \times \text{actual } CH_4 \text{ (g/day)} \ (r^2 = 0.631, S_{yx} = 39.3)$$

CH_4 (g/day) = 1.385(±0.036) × actual CH_4 (g/day) (r^2 = 0.940, S_{yx} = 39.71)

These equations compare to the following regression analysis of the enteric CH_4 prediction equations recommended by NASEM (2016) for high-concentrate beef cattle diets:

Escobar et al. (n.d.): predicted CH_4 (g/day) = -24.63(± 13.32) + 1.798(± 0.133) × actual CH_4 (g/day) (r^2 = 0.655, S_{yx} = 45.00)

Ellis et al. (2007), equation 9b: predicted MJ/d = -1.978(±1.073) + 3.494(±0.470) × actual MJ/day (r^2 = 0.363, S_{yx} = 1.85)

Ellis et al. (2007), equation 10b: predicted MJ/d = 1.514(±0.499) + 0.961(± 0.103) × actual MJ/day (r^2 = 0.474, S_{yx} = 1.682)

Ellis et al. (2009), equation G: predicted MJ/d = 2.189(±0.416) + 0.673(±0.069) × actual MJ/day (r^2 = 0.493, S_{yx} = 1.651)

The predicted versus actually determined values for the proposed model and the equations proposed by NASEM (2016) are presented in table 4B-1.

Table 4B-1. Actual vs. Predicted Enteric CH_4 Emissions From Feedlot Beef Cattle Using the Proposed Model and Four Equations Proposed by NASEM (2016)

Equation	Units	Actual	Predicted
Proposed model	g/d	137.7±54.8	148.0±64.1
Proposed model	% of gross energy	4.36±1.38	4.55±0.78
Escobar et al. (unpublished)	g/d	137.7±54.8	93.66±34.41
Ellis et al. (2007), equation 9b	MJ/d	7.69±3.07	2.246±0.401
Ellis et al. (2007), equation 10	MJ/d	7.69±3.07	4.534±1.662
Ellis et al. (2009), equation G	MJ/d	7.69±3.07	5.469±2.420

The Lin's concordance statistics for the new model and the NASEM (2016) equations are as follows. In some cases, the extant NASEM (2016) equations appeared to be equal to or better than the proposed model. This may be due in part to the fact that some of the data used in the testing dataset were also used in the development dataset for those models.

Table 4B-2. Lin's Concordance Statistics for the Proposed Feedlot Beef Cattle Model and Four Models Proposed by NASEM (2016)

Statistic	This Model (Y_m)	This Model (CH_4, g/day)	Escobar (g/day)	Ellis Eq. 9b (MJ/day)	Ellis Eq. 10b (MJ/day)	Ellis Eq. G (MJ/day)
r	0.464	0.794	-0.15	0.608	0.692	0.706
CCC	0.390	0.549	-0.002	0.060	0.538	0.695
Lower CI	0.249	0.448	-0.004	0.038	0.418	0.577
Upper CI	0.515	0.637	0.005	0.083	0.639	0.785
r^2	0.215	0.631	0.024	0.370	0.479	0.498
Location shift	0.182	0.834	13.26	-3.77	-0.68	-0.17
Scale shift	0.562	1.552	26.15	0.175	0.72	1.05
C_b, bias feature	0.843	0.692	0.010	0.010	0.776	0.985

Effect of Ionophores Adjustment

The published effects of ionophores such as monensin on enteric CH_4 emissions have been somewhat inconsistent. Tedeschi et al. (2003), McGinn et al. (2004), Guan et al. (2006), and Hemphill et al. (2018) suggested that monensin decreased CH_4 emissions from 5 to 20 percent during the first 4 weeks of feeding, but that the effect was transient and lasted only about 30 days. However, a meta-analysis by Appuhamy et al. (2013) reported that monensin decreased Y_m of beef cattle about 0.3 units (14–19 g CH_4/d) and that the effect did not significantly change over the 15- to 180-day feeding periods. Therefore, the authors assumed monensin decreased the Y_m of finishing beef cattle by 0.3 units.

Effect of Dietary Fat Concentration Adjustment

Increased dietary fat concentration tends to decrease enteric CH_4 emissions from 3.8 to 5.6 percent for each percentage unit increase in dietary fat concentration (Beauchemin et al., 2008; Martin et al., 2010; Zinn and Shen, 1996). Lovett et al. (2003) reported that total daily CH_4 emissions decreased from 0.19 to 0.12 kg/animal daily (reported as 260 vs. 172 L CH_4/head daily, or 6.6 vs. 4.8 percent of GEI) from steers fed diets containing 0 or 350 grams of coconut oil, respectively. The effect was consistent across various forage concentrations (65:40 and 10 percent of dry matter). More recently Hales et al. (2017b) noted a linear decrease in enteric CH_4 emissions (i.e., Y_m) of finishing beef cattle (decreased from 3.39 to 2.23 percent; about 5.7 percent/percent added fat) in cattle fed finishing diets that contained 0, 2, 4, and 6 percent added corn oil. Many byproduct feeds such as distillers grains contain relatively high concentrations of fat (generally as corn oil) and this fat may be partially protected from ruminal biohydrogenation (Corrigan et al., 2009; Vander Pol et al., 2009); however, the fat in distillers grains is assumed to have the same effect on enteric CH_4 as added corn oil/fat. This assumption is supported by the studies of Hunerberg et al. (2013, 2014) and McGinn et al. (2009) who reported about a 6.7-percent decrease in enteric Y_m for each percentage unit increase in dietary total fat added by distillers grains. Hunerberg et al. (2014) suggested that the maximum effect of fat on Y_m of beef cattle was limited to a 12-percent decrease. In addition, cattle have a low tolerance for dietary lipids; therefore, dietary concentrations are generally kept below 8 percent total fat. The authors opted to use the conservative estimate of a 4-percent increase in enteric CH_4 for each 1-percent decrease in dietary fat below the baseline values of 3 percent added fat and 6 percent total fat and assumed adding fat above the 6 percent total fat baseline did not affect enteric CH_4 production any further.

Dietary Grain Source and Processing Method Adjustment

There are few studies comparing the enteric CH_4 production of cattle fed high concentrate diets based on different grain sources and different gain processing methods. Based on the rumen stoichiometry of Wolin (1960), Zinn and Barajas (1997) estimated that CH_4 emissions per unit of glucose fermented in the rumen would decrease with increasing grain processing intensity. Hales et al. (2012) reported that cattle fed diets based on steam-flaked corn had enteric CH_4 production that was 20 percent lower than cattle fed diets based on dry-rolled corn. This relationship was consistent when diets contained 0 and 30 percent wet distillers grains with solubles (WDGS). Archibeque et al. (2006) noted a similar difference between CH_4 production of cattle fed dry-rolled corn and high-moisture corn finishing diets. In contrast, Hales et al. (2015b) reported no difference in CH_4 production of finishing cattle fed diets based on dry-rolled corn or high-moisture corn. However, the starch digestibility of the high-moisture corn was very low in the study by Hales et al. (2015b), suggesting the high-moisture corn was not representative of high-moisture corn in the industry. Therefore, the authors assumed cattle fed high moisture corn-based diets would have enteric Y_m similar to cattle fed steam-flaked corn-based diets. In addition, because steam flaking has little effect on digestibility of barley (Owens et al., 1997) the authors assumed that steam flaking would not affect enteric Y_m of finishing cattle fed barley-based diets. Because some producers use blends of grain processed in different manners the authors assumed that any steam flaking effects should be based on the proportion (percent of the grain) that is steam flaked.

Enteric CH_4 emissions are 20 to 40 percent greater with finishing diets that are based on barley rather than corn, probably because of the differences in fiber content between the grains (Benchaar et al., 2001; Beauchemin and McGinn, 2005). In the USDA-OCE (2014) model, the authors assumed a mean increase of 30 percent in enteric Y_m when barley replaced corn as the grain source in the diet. However, in the revised model the effect of barley replacement is considered in the starch:NDF ratio of the diet, so the effect of barley is not adjusted directly.

Dietary Starch:NDF Ratio Adjustment

It is well established that increasing fiber content of ruminant diets tends to increase Y_m, whereas increasing the starch content tends to decrease Y_m. Little data exists to evaluate the effects of diet forage content on Y_m in high-concentrate finishing diets. The authors of the 2014 model (USDA 2014) developed a correction factor for dietary concentrate content based on equations of Ellis et al. (2007, 2009). In this new model, the authors chose to base the correction factor on the starch:NDF ratio of the diet. In feedlot finishing diets, the fiber (i.e., NDF) and starch content of diets can be modified by replacing corn with barley, replacing grain with forage, or replacing grain with high-fiber grain-based byproducts such as WDGS (Samuelson et al., 2016). Limited data exists to evaluate effects of dietary barley, forage, WDGS, and grain concentrations or their ratios on enteric CH_4 production from beef cattle that are fed typical U.S.-based, high-concentrate finishing diets. Therefore, the authors developed a dataset consisting of 4 published studies (Beauchemin and McGinn, 2005; Hales et al., 2012, 2013, 2014) and 14 treatment means. In these studies, the dietary starch:NDF ratio was modified by replacing corn with either barley (Beauchemin and McGinn, 2005) or forage (Hales et al., 2014), by changing the roughage source (barley vs. corn silage: Beauchemin and McGinn, 2005), or by replacing a portion (0 to 45 percent) of the corn with WDGS (Hales et al., 2012, 2013). In all studies dietary fat concentrations were equalized across treatments. Simple linear regression was performed to determine the effects of forage percentage, dietary NDF percent, dietary starch percent, and the starch:NDF ratio on the Y_m. The equation for dietary NDF concentration had the greatest r^2 (0.72) and lowest S_{yx} (0.432), followed closely by the starch:NDF ratio (r^2 = 0.66 and S_{yx} = 0.47). Because the dietary NDF concentration is confounded by simultaneous changes in dietary starch content, the authors felt the starch:NDF ratio was more biologically explainable, and thus the starch:NDF ratio was selected. The equation developed was as follows:

$$Y_m = 4.514\ (\pm 0.472) - 0.453\ (\pm 0.148) \times starch{:}NDF$$

Therefore, the authors assumed that Y_m changed 0.453 units for each unit change in the starch:NDF ratio.

4-B.3 Enteric Methane Emissions From Sheep

4-B.3.1 Rationale for Method

The following subsections describe the rationale for the methodologies presented within the chapter for sheep. In terms of uncertainty, IPCC continues to recommend the use of IPCC 2006 Tier 1 uncertainty ranges as defined in IPCC (2019), IPCC section 10.3.4.

Estimating Enteric Methane Emissions From Sheep

Howden et al. (1994) generated an equation from which to predict CH_4 emissions from sheep, included in this chapter as equation 4-13. This equation resulted from a linear extrapolation of DMI to emissions. It has since been evaluated, found to be robust, and selected by the Australian National GHG Inventory. Klein and Wright (2006) measured CH_4 from sheep in respiration chambers and compared their results to the Howden equation. Actual CH_4 averaged 1.1 g/head (standard error ± 0.05) and predicted CH_4 was 1.1 g/head (standard error ± 0.02). A potential concern about the Howden equation is that much of the data included in the analysis was based on tropical forages.

Nonetheless, when intake data are available, the Howden equation presents the best method by which to estimate sheep enteric CH_4 emissions.

Estimating Enteric Methane Emissions From Sheep If Intake Is Not Known

If there is no intake data available, the revised (IPCC, 2019) equations can be used. The revision considers new data submitted from New Zealand and Australia that results from measurements from sheep housed in respiration calorimetry chambers.

4-B.4 Enteric Methane Emissions From Swine

Due to the small amount of enteric CH_4 emissions generated from swine and a lack of data for estimating Tier 2 emission factors, the authors recommend using the IPCC Tier 1 methodology.

In terms of uncertainty, for swine, the recommended CH_4 estimation methods for emissions from enteric fermentation are based on the IPCC Tier 1 approach, which has an uncertainty of ±30 to 50 percent.

4-B.5 Enteric Methane Emissions From Goats

The proposed method is the best option for calculating emissions at the entity level. These data came from an analysis of 65 studies in which CH_4 emissions were measured or calculated. Many of the studies were from areas of the world that manage goats very differently than in the United States. Nonetheless, the compiled Y_m value, 5.5 ± 1.0 percent is not much different than Y_m values from measurements conducted in the United States.

In terms of uncertainty, for goats, the recommended estimation methods for enteric CH_4 emissions are based on the IPCC Tier 1 approach, which has an uncertainty of ±30 to 50 percent.

4-B.6 Enteric Methane Emissions From American Bison

The U.S. EPA uses IPCC Tier 1 methodologies to estimate bison emissions (U.S. EPA, 2020), and currently Tier 1 is the best option to estimate enteric CH_4 emissions for bison. Galbraith et al. (1998) measured enteric CH_4 from growing bison (n=5) fed alfalfa pellets in the winter–spring (February–March) and spring (April–May) using respiration calorimetry chambers. The bison produced an average of 86.4 g/day (6.6 percent GEI). Using a detailed method of calculation to estimate historical bison emissions, Kelliher and Clark (2010) estimated that grazing bison would produce 72 kg CH_4/year or 197 g CH_4/day. Hristov (2012) estimated present day bison produce 21 g CH_4/kg DMI/day, eat about 12.8 kg DM/day, and produce 268 g CH_4/day. The differences between these estimates result from differences in animal weights, DMI, limited measurements of bison emissions, and assumed MCFs.

In terms of uncertainty, for American bison the recommended estimation methods for enteric CH_4 emissions are based on the IPCC Tier 1 approach, which has an uncertainty of ±30 to 50 percent.

4-B.7 Enteric Methane Emissions From Other Animals (Deer, Llamas, Alpaca, Elk)

Currently the IPCC Tier 1 methodology is the best option to estimate enteric CH_4 emissions from llamas, alpaca and deer. Galbraith et al. (1998) measured enteric CH_4 from white-tailed deer (n=8) fed alfalfa pellets in the winter–spring (February–March) and spring (April–May) using respiration calorimetry chambers. The deer produced an average of 23.6 g/day CH_4 (3.3 percent GEI). The New Zealand Ministry for the Environment (2010) uses a factor of 6.4 percent of GEI to predict enteric CH_4 emissions from farmed red deer and projects an emission rate per year of 23.7 kg CH_4/head/year. The values used to make these calculations are from measurements of deer CH_4 emissions using the SF_6 tracer method. Elk, white-tailed, and mule deer enteric CH_4 emissions were estimated by Hristov (2012) to be 86.4, 16, and 17 g CH_4/head/day respectively.

In terms of uncertainty, for llamas, alpacas, and managed wildlife (including deer), the recommended estimation methods for enteric CH_4 emissions are based on the IPCC Tier 1 approach, which has an uncertainty of ±30 to 50 percent.

4-B.8 Housing and Manure Management Emissions

4-B.8.1 Rationale for Methods

The rationale for housing and manure management method section is presented below in table 4 B-3.

Table 4B-3. Housing and Manure Management Emission Methodology Documentation

Housing and Manure Management Parameters	Recommended Method
Estimating CH_4 Emissions From Freestall Dairy Barn Floors	The only published equation for estimating CH_4 emissions from barn floors was developed by Chianese et al. (2009).
CH_4 Emissions From Housing and Manure Storage	The IPCC (2019) equation for estimating CH_4 emissions from manure in housing and storage was used.
Daily VS Excretion Rates	The IPCC (2019) equation for estimating VS excretion was used.
N_2O Emissions From Housing	The IPCC (2019) equation for estimating N_2O emissions from manure in housing and storage was used.
Total Nitrogen Entering Manure Storage and Treatment	Total N entering manure is based on professional judgment regarding N losses from housing and ammonia emissions data developed for a variety of housing in the United States (Koelsch and Stowell, 2005)
Nitrogen Excretion From Lactating Cows	The equation by Bougouin et al. (2022) is based on a current meta-analysis and has performed well for lactating cows in the United States.
Nitrogen Excretion From Nonlactating Cows and Heifers	Equation by Reed et al. (2015) represents the most up to date estimates for N excretion. The simpler equation based on nitrogen intake developed by Reed et al. (2015) to predict total manure nitrogen in heifers and nonlactating cows consistently outperformed more complex equations.

Housing and Manure Management Parameters	Recommended Method
Nitrogen Excretion From Feedlot Cattle	Equation by Dong et al. (2014) represents the most up to date estimates for N excretion. When feed intake is unknown, the equation for DMI as a percent of body weight and kg/day by Anele et al. (2014), and subsequently NASEM (2016), are the most complete estimate.
Monthly Beef Feedlot NH_3 Emissions	The equation by Todd et al. (2013) is based on empirical data collected on farm and is the most robust estimation.
Nitrogen Excretion From Swine	The IPCC (2019) equation for estimating N excretion was used.
Nitrogen Excretion From Growing Pigs	The IPCC (2019) equation for estimating N excretion was used.
Nitrogen Excretion From Breeding Sows	The IPCC (2019) equation for estimating N excretion was used.
Nitrogen Excretion From Poultry Produced for Meat	The IPCC (2019) equation for estimating N excretion was used.
Nitrogen Excretion From Egg Laying Poultry	The IPCC (2019) equation for estimating N excretion was used.
IPCC Tier 2 Approach for Estimating N_2O Emissions Manure Storage	The IPCC (2019) equation for estimating N_2O emissions from manure in housing and storage was used.
N_2O Emissions From Anaerobic Lagoon, Runoff Holding Ponds, and Storage Tanks	The most readily available option, an EF developed in the United States based on lagoon surface area was used.
CH_4 Emissions From Anaerobic Digesters	The IPCC (2019) equation for estimating CH_4 emissions from anaerobic digesters was used.

4-B.8.2 Technical Documentation

Housing Uncertainty

Current available default values of uncertainty for dairy housing are listed in table 4B-4.

Table 4B-4. Available Uncertainty Information for Activity and Ancillary Data Used to Estimate Emissions From Dairy Housing

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Maximum CH_4 producing capacities—dairy replacement	B_0	m^3 CH_4/kg VS	0.17	-20	20	IPCC (2019)
Maximum CH_4 producing capacities—dairy cow	B_0	m^3 CH_4/kg VS	0.24	-20	20	IPCC (2019)
VS—dairy replacement	VS	kg/1,000 kg animal mass/day	9.3	-20	20	IPCC (2019)
VS—dairy cattle	VS	kg/1,000 kg animal mass/day	9.3	-20	20	IPCC (2019)
MCF—dairy cow	MCF	%	Varies	-30	30	IPCC (2019)

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Typical NH_3 losses from dairy housing facilities—dry lot including housing with barn and lot combination	NH_3 loss	% of N_{ex}	36	—	—	Bougouin et al. (2016), Hristov et al. (2011), Liu et al. (2017)
Typical NH_3 losses from dairy housing facilities—barn (natural or mechanical ventilation)	NH_3 loss	% of N_{ex}	15.5	—	—	Bougouin et al. (2016), Hristov et al. (2011), Liu et al. (2017)
Typical NH_3 losses from dairy housing facilities—roofed facility (bedded pack, no mix)	NH_3 loss	% of N_{ex}	25	-60	20	IPCC (2019)
Typical NH_3 losses from dairy housing facilities—roofed facility (bedded pack, active mix)	NH_3 loss	% of N_{ex}	50	-86	20	IPCC (2019)
Typical NH_3 losses from dairy housing facilities—pasture	NH_3 loss	% of N_{ex}	7	—	—	Voglmeier et al. (2018), Sommer et al. (2019), Adhikari et al. (2020), Fischer et al. (2015)
Typical N leaching losses from dairy housing facilities—dry lot including housing with barn and lot combination	N leaching loss	% of N_{ex}	3.5	-100	100	IPCC (2019)
Typical N leaching losses from dairy housing facilities—barn (natural or mechanical ventilation)	N leaching loss	% of N_{ex}	0	—	—	IPCC (2019)
Typical NH_3 losses from dairy housing facilities—bedded pack (no mix)	N leaching loss	% of N_{ex}	3.5	-100	100	IPCC (2019)
Typical NH_3 losses from dairy housing facilities—bedded pack (active mix)	N leaching loss	% of N_{ex}	3.5	-100	100	IPCC (2019)
Typical NH_3 losses from dairy housing facilities—pasture	N leaching loss	% of N_{ex}	—	—	—	
N_2O emission factor for dairy housing facilities—open dry lots	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.02	-100	100	IPCC (2019)

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
N_2O emission factor for dairy housing facilities—roofed facility—pit below animal confinement	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.002	-100	100	IPCC (2019)
N_2O emission factor for dairy housing facilities—roofed facility—bedded pack (no mix)	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.01	-100	100	IPCC (2019)
N_2O emission factor for dairy housing facilities—roofed facility—bedded pack (active mix)	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.07	-100	100	IPCC (2019)
N_2O emission factor for dairy housing facilities—roofed facility—compost barn	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.005	-100	100	IPCC (2019)

All default values have a triangular distribution.

The authors chose the most accurate empirical equations by evaluating the root mean square error to assess prediction accuracy and other available model performance indicators to assess bias. The corresponding root mean square error and coefficient of determination are 0.121 and 0.62, respectively, for equation 4-27, while the root mean square error and coefficient of determination are 0.44 and 0.88, respectively, for equation 4-28.

Current available default values of uncertainty for beef housing are listed in table 4B-5.

Table 4B-5. Available Uncertainty Data for Emissions From Beef Cattle Housing

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Maximum CH_4 producing capacities—mature beef cows	B_0	m^3 CH_4/kg VS	0.33	-20	20	IPCC (2019)
Maximum CH_4 producing capacities—steers (> 500 lbs)	B_0	m^3 CH_4/kg VS	0.33	-20	20	IPCC (2019)
Maximum CH_4 producing capacities—stockers (all)	B_0	m^3 CH_4/kg VS	0.17	-20	20	IPCC (2019)
Maximum CH_4 producing capacities—cattle on feed	B_0	m^3 CH_4/kg VS	0.33	-20	20	IPCC (2019)
Maximum CH_4 producing capacities—cattle	B_0	m^3 CH_4/kg VS	0.19	-20	20	IPCC (2019)
VS rate—all beef cattle	VS	kg/1,000 kg animal mass/day	7.6	-20	20	IPCC (2019)
MCF—beef cattle	MCF	%	Varies	-30	30	IPCC (2019)

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Typical NH_3 losses from beef housing facilities—feedlot/dry lot	NH_3 loss	% of N_{ex}	65	—	—	Hristov et al. (2011), Liu et al. (2017)
Typical NH_3 losses from beef housing facilities—bedded pack (no mix)	NH_3 loss	% of N_{ex}	25	-60	20	IPCC (2019)
Typical NH_3 losses from beef housing facilities—bedded pack (active mix)	NH_3 loss	% of N_{ex}	60	-80	8	IPCC (2019)
Typical NH_3 losses from beef housing facilities—pasture	NH_3 loss	% of N_{ex}	7	—	—	Voglmeier et al. (2018), Sommer et al. (2019), Adhikari et al. (2020), Fischer et al. (2015)
Typical N leaching losses from beef housing facilities—feedlot/dry lot	N leaching loss	% of N_{ex}	3.5	-100	100	IPCC (2019)
Typical N leaching losses from beef housing facilities—bedded pack (no mix)	N leaching loss	% of N_{ex}	3.5	-100	100	IPCC (2019)
Typical N leaching losses from beef housing facilities—bedded pack (active mix)	N leaching loss	% of N_{ex}	3.5	-100	100	IPCC (2019)
Typical N leaching losses from beef housing facilities—pasture	N leaching loss	% of N_{ex}	—	—	—	
N_2O emission factor for beef housing facilities—open dry lots	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.02	-100	100	IPCC (2019)
N_2O emission factor for beef housing facilities—roofed facility—bedded pack (no mix)	EF_{N2O}	kg N_2O-N/ kg N_{ex}	0.01	-100	100	IPCC (2019)
N_2O emission factor for beef housing facilities—roofed facility—bedded pack (active mix)	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.07	-100	100	IPCC (2019)
N_2O emission factor for beef housing facilities—roofed facility (compost barn)	EF_{N2O}	kg N2O-N/kg Nex	0.005	-100	100	IPCC (2019)

All default values have a triangular distribution.

Current available default values of uncertainty for GHG emission estimation of swine housing are listed in table 4B-6.

Table 4B-6. Available Uncertainty Data for Emissions From Swine Housing

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Maximum CH_4 producing capacities—growing swine	B_0	m^3 CH_4/kg VS	0.48	-30	30	IPCC (2019)
Maximum CH_4 producing capacities—breeding swine	B_0	m^3 CH_4/kg VS	0.48	-30	30	IPCC (2019)
VS—growing swine	VS	kg/1,000 kg animal mass	3.9	-20	20	IPCC (2019)
VS—breeding swine	VS	kg/1,000 kg animal mass	1.8	-20	20	IPCC (2019)
MCF—swine	MCF	%	Varies	-30	30	IPCC (2019)
Nitrogen gain—nursery (4–7 kg)	N_{gain}	kg N/kg BW	0.031			IPCC (2019)
Nitrogen gain—nursery (7–20 kg)	N_{gain}	kg N/kg BW	0.028			IPCC (2019)
Nitrogen gain—grower (20–40 kg)	N_{gain}	kg N/kg BW	0.025			IPCC (2019)
Nitrogen gain—grower (40–80 kg)	N_{gain}	kg N/kg BW	0.024			IPCC (2019)
Nitrogen gain—finisher (80–120 kg)	N_{gain}	kg N/kg BW	0.021			IPCC (2019)
Typical NH_3 losses from swine housing facilities—roofed facility (bedded pack, no mix)	NH_3 loss	% of N_{ex}	40	-75	50	IPCC (2019)
Typical NH_3 losses from swine housing facilities—roofed facility (bedded pack, active mix), including compost barns	NH_3 loss	% of N_{ex}	65	-78	8	IPCC (2019)
Typical NH_3 losses from swine housing facilities—roofed facility (pit under floor)	NH_3 loss	% of N_{ex}	25	-40	20	IPCC (2019)
Typical NH_3 losses from swine housing facilities—pasture	NH_3 loss	% of N_{ex}	19	—	—	Sommer et al. (2019)
Typical N leaching losses from swine housing facilities—roofed facility (bedded pack, no mix)	N leaching loss	% of N_{ex}	3.5	-100	100	IPCC (2019)

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Typical N leaching losses from swine housing facilities—roofed facility (bedded pack, active mix), including compost barns	N leaching loss	% of N_{ex}	3.5	-100	100	IPCC (2019)
Typical N leaching losses from swine housing facilities—roofed facility (pit under floor)	N leaching loss	% of N_{ex}	0	—	—	IPCC (2019)
Typical N leaching losses from swine housing facilities—pasture	N leaching loss	% of N_{ex}	—	—	—	
N_2O emission factor for swine housing facilities—pit storage under confinement	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.002	-100	100	IPCC (2019)
N_2O emission factor for swine housing facilities—roofed facility—bedded pack (no mix)	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.01	-100	100	IPCC (2019)
N_2O emission factor for swine housing facilities—roofed facility—bedded pack (active mix)	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.07	-100	100	IPCC (2019)
N_2O emission factor for swine housing facilities—roofed facility (compost barn)	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.005	-100	100	IPCC (2019)

All default values have a triangular distribution.

Current available default values of uncertainty for greenhouse emission estimation of poultry housing are listed in table 4B-7.

Table 4B-7. Available Uncertainty Data for Emissions From Poultry Housing

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Maximum CH_4 producing capacities—layer poultry	B_0	m^3 CH_4/kg VS	0.39	-15	15	IPCC (2019)
Maximum CH_4 producing capacities—meat poultry	B_0	m^3 CH_4/kg VS	0.36	-15	15	IPCC (2019)
VS—layer poultry	VS	kg/1,000 kg animal mass	9.4	-20	20	IPCC (2019)
VS—meat poultry	VS	kg/1,000 kg animal mass	16.8	-20	20	IPCC (2019)
MCF—poultry manure with and without litter	MCF	%	Varies	-30	30	IPCC (2019)

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Typical NH_3 losses from poultry housing—roofed facility—with litter	NH_3 loss	% of N_{ex}	40	-75	50	Koelsch and Stowell (2005)
Typical NH_3 losses from poultry housing—roofed facility—without litter	NH_3 loss	% of N_{ex}	48	-69	25	IPCC (2019)
Typical NH_3 losses from poultry housing—use of alum or another acidifying agent in litter	NH_3 loss	% of N_{ex}	20	—	—	Anderson et al. (2020), Eugene et al. (2015), Madrid et al. (2012), and Moore et al. (2008)

All default values have a triangular distribution.

Current available default values of uncertainty for greenhouse emission estimation of other animal housing are listed in table 4B-8.

Table 4B-8. Available Uncertainty Data for Emissions From Other Animal Housing

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Maximum CH_4 producing capacities—other animals	B_0	m^3 CH_4/kg VS	Varies	-15	15	IPCC (2019)
MCF—other animals	MCF	%	Varies	-30	30	IPCC (2019)
VS—other animals	VS	kg/1,000 kg animal mass	Varies	-20	20	IPCC (2019)
Typical NH_3 losses from dry lot housing	NH_3 loss	% of N_{ex}	Varies	-100	100	IPCC (2019)

Manure Management Uncertainty

Current default values of uncertainty for temporary and long-term stockpile storage are listed in table 4B-9.

Table 4B-9. Available Uncertainty Data for Emissions From Solid Storage

Parameter	Variable	Data Input Unit	Default Value	Relative Uncertainty Low (%)	Relative Uncertainty High (%)	Data Source
Maximum CH_4 producing capacities	B_0	m^3 CH_4/kg VS	—	-15	15	IPCC (2019)
MCF—solid storage	MCF	%	—	-30	30	IPCC (2019)

Parameter	Variable	Data Input Unit	Default Value	Relative Uncertainty Low (%)	Relative Uncertainty High (%)	Data Source
N_2O emission factor—storage of solid manure	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.01	-100	100	IPCC (2019)
N_2O emission factor—solid storage covered/compacted	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.01	-100	100	IPCC (2019)
N_2O emission factor—solid storage bulking agent added	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.005	-100	100	IPCC (2019)
N_2O emission factor—solid storage additives	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.005	-100	100	IPCC (2019)
Typical NH_3 losses from solid storage of manure (swine, other cattle)	NH_3 loss	% of N_{ex}	45	-78	44	IPCC (2019)
Typical NH_3 losses from solid storage of manure (dairy cow)	NH_3 loss	% of N_{ex}	30	-67	33	IPCC (2019)
Typical NH_3 losses from solid storage of manure (poultry)	NH_3 loss	% of N_{ex}	40	-70	50	IPCC (2019)
Typical NH_3 losses from solid storage of manure (other animals)	NH_3 loss	% of N_{ex}	12	-58	67	IPCC (2019)
Typical NH_3 losses from solid storage covered/compacted (swine)	NH_3 loss	% of N_{ex}	22	-82	18	IPCC (2019)
Typical NH_3 losses from solid storage covered/compacted (other cattle)	NH_3 loss	% of N_{ex}	22	-86	18	IPCC (2019)
Typical NH_3 losses from solid storage covered/compacted (dairy cow)	NH_3 loss	% of N_{ex}	14	-86	21	IPCC (2019)
Typical NH_3 losses from solid storage covered/compacted (poultry)	NH_3 loss	% of N_{ex}	20	-80	20	IPCC (2019)
Typical NH_3 losses from solid storage covered/compacted (other animals)	NH_3 loss	% of N_{ex}	5	-100	40	IPCC (2019)
Typical NH_3 losses from solid storage bulking agent added (swine)	NH_3 loss	% of N_{ex}	58	-81	21	IPCC (2019)
Typical NH_3 losses from solid storage bulking agent added (other cattle)	NH_3 loss	% of N_{ex}	58	-86	21	IPCC (2019)
Typical NH_3 losses from solid storage bulking agent added (dairy cow)	NH_3 loss	% of N_{ex}	38	-84	21	IPCC (2019)
Typical NH_3 losses from solid storage bulking agent added (poultry)	NH_3 loss	% of N_{ex}	54	-81	20	IPCC (2019)

Parameter	Variable	Data Input Unit	Default Value	Relative Uncertainty Low (%)	Relative Uncertainty High (%)	Data Source
Typical NH_3 losses from solid storage bulking agent added (other animals)	NH_3 loss	% of N_{ex}	15	-60	20	IPCC (2019)
Typical NH_3 losses from solid storage additives (swine)	NH_3 loss	% of N_{ex}	17	-82	24	IPCC (2019)
Typical NH_3 losses from solid storage additives (other cattle)	NH_3 loss	% of N_{ex}	17	-88	24	IPCC (2019)
Typical NH_3 losses from solid storage additives (dairy cow)	NH_3 loss	% of N_{ex}	11	-91	27	IPCC (2019)
Typical NH_3 losses from solid storage additives (poultry)	NH_3 loss	% of N_{ex}	16	-81	25	IPCC (2019)
Typical NH_3 losses from solid storage additives (other animals)	NH_3 loss	% of N_{ex}	4	-75	25	IPCC (2019)
Typical N leaching losses from solid storage of manure	N leaching loss	% of N_{ex}	2	—	—	IPCC (2019)
Typical N leaching losses from solid storage covered/compacted	N leaching loss	% of N_{ex}	0	—	—	IPCC (2019)
Typical N leaching losses from solid storage bulking agent added	N leaching loss	% of N_{ex}	2	—	—	IPCC (2019)
Typical N leaching losses from solid storage additives	N leaching loss	% of N_{ex}	2	—	—	IPCC (2019)

All default values have a triangular distribution.

Table 4B-10 lists confidence intervals for emission factors and input variables for the activity data used for composting, based on IPCC's estimation.

Table 4B-10. Available Uncertainty Data for Emissions From Manure Composting

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Maximum CH_4 producing capacities	B_0	m^3 CH_4/kg VS	Varies	-15	15	IPCC (2019)
MCF—solid storage—composting	MCF	%	Varies	-30	30	IPCC (2019)
N_2O emission factor—composting (in-vessel)	EF_{N2O}	kg N_2O-N/kg	0.006	-100	100	IPCC (2019)
N_2O emission factor—composting (static pile)	EF_{N2O}	kg N_2O-N/kg	0.01	-100	100	IPCC (2019)

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
N_2O emission factor—composting (intensive windrow)	EF_{N2O}	kg N_2O-N/kg	0.005	-100	100	IPCC (2019)
N_2O emission factor—composting (passive windrow)	EF_{N2O}	kg N_2O-N/kg	0.005	-100	100	IPCC (2019)
Typical NH_3 losses from composting (in-vessel) (swine, poultry, and other cattle)	NH_3 loss	% of N_{ex}	60	-80	8	IPCC (2019)
Typical NH_3 losses from composting (in-vessel) (dairy cow)	NH_3 loss	% of N_{ex}	45	-84	20	IPCC (2019)
Typical NH_3 losses from composting (in-vessel) (other animal)	NH_3 loss	% of N_{ex}	18	-78	17	IPCC (2019)
Typical NH_3 losses from composting (static pile) (swine, poultry, and other cattle)	NH_3 loss	% of N_{ex}	65	-78	8	IPCC (2019)
Typical NH_3 losses from composting (static pile) (dairy cow)	NH_3 loss	% of N_{ex}	50	-86	20	IPCC (2019)
Typical NH_3 losses from composting (static pile) (other animal)	NH_3 loss	% of N_{ex}	20	-75	20	IPCC (2019)
Typical NH_3 losses from composting (intensive windrow) (swine, poultry, and other cattle)	NH_3 loss	% of N_{ex}	65	-78	8	IPCC (2019)
Typical NH_3 losses from composting (intensive windrow) (dairy cow)	NH_3 loss	% of N_{ex}	50	-86	20	IPCC (2019)
Typical NH_3 losses from composting (intensive windrow) (other animal)	NH_3 loss	% of N_{ex}	20	-75	20	IPCC (2019)
Typical NH_3 losses from composting (passive windrow) (swine, poultry, and other cattle)	NH_3 loss	% of N_{ex}	60	-80	8	IPCC (2019)
Typical NH_3 losses from composting (passive windrow) (dairy cow)	NH_3 loss	% of N_{ex}	45	-84	20	IPCC (2019)
Typical NH_3 losses from composting (passive windrow) (other animal)	NH_3 loss	% of N_{ex}	18	-78	17	IPCC (2019)

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Typical N leaching losses composting (in-vessel)	N leaching loss	% of N_{ex}	0	—	—	IPCC (2019)
Typical N leaching losses from composting (static pile)	N leaching loss	% of N_{ex}	6	—	—	IPCC (2019)
Typical N leaching losses from composting (intensive windrow)	N leaching loss	% of N_{ex}	6	—	—	IPCC (2019)
Typical N leaching losses from composting (passive windrow)	N leaching loss	% of N_{ex}	4	—	—	IPCC (2019)

All default values have a triangular distribution.

Table 4B-11 lists confidence intervals for emission factors and input variables for the activity data used for aerobic lagoons, based on IPCC's estimation.

Table 4B-11. Available Uncertainty Data for Aerobic Lagoon Emission Factors

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
N_2O emission factor—aerobic lagoon—natural aeration	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.01	-100	100	IPCC (2019)
N_2O emission factor—aerobic lagoon—forced aeration	EF_{N2O}	kg N_2O-N/kg N_{ex}	0.005	-100	100	IPCC (2019)
Typical NH_3 losses from aerobic lagoon—natural aeration (swine, dairy, and other cattle)	NH_3 loss	% of N_{ex}	—	—	—	IPCC (2019)
Typical NH_3 losses from aerobic lagoon—forced aeration (swine, dairy, and other cattle)	NH_3 loss	% of N_{ex}	85	-68	18	IPCC (2019)
Typical NH_3 losses aerobic lagoon—forced aeration (other animals)	NH_3 loss	% of N_{ex}	27	—	—	IPCC (2019)
Typical N leaching losses from aerobic lagoon—natural aeration	N leaching loss	% of N_{ex}	0	—	—	IPCC (2019)

Parameter	Variable	Data Input Unit	Default Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Typical N leaching aerobic lagoon—forced aeration	N leaching loss	% of N_{ex}	0	—	—	—

All default values have a triangular distribution.

Table 4B-12 lists confidence intervals for emission factors and input variables for the activity data used for liquid manure storage, based on IPCC's estimation.

Table 4B-12. Available Uncertainty Data for Anaerobic Lagoons, Runoff Holding Ponds, and Storage Tanks Emission Factors

Parameter	Variable	Data Input Unit	Estimated Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Anaerobic lagoon, runoff holding ponds, and storage tanks—N_2O emission factor	EF_{N2O}	kg N_2O-N/kg N_{ex}	Varies	-100	100	IPCC (2019)
Anaerobic lagoon, runoff holding ponds, and storage tanks—MCF	MCF	kg CH_4/kg VS	Varies	-100	100	IPCC (2019)
Typical NH_3 losses from anaerobic lagoon (swine, poultry)	NH_3 loss	% of N_{ex}	40	-38	88	IPCC (2019)
Typical NH_3 losses from anaerobic lagoon (dairy, other cattle, and other animals)	NH_3 loss	% of N_{ex}	35	-43	129	IPCC (2019)
Typical NH_3 losses from anaerobic digester	NH_3 loss	% of N_{ex}	Varies	—	—	IPCC (2019)
Typical NH_3 losses from liquid/slurry—with natural crust over (swine, dairy cow, other cattle)	NH_3 loss	% of N_{ex}	30	-70	20	IPCC (2019)
Typical NH_3 losses from liquid/slurry—with natural crust over (other animals)	NH_3 loss	% of N_{ex}	9	—	—	IPCC (2019)
Typical NH_3 losses from liquid/slurry—without natural crust cover (swine, dairy cow, other cattle)	NH_3 loss	% of N_{ex}	48	-69	25	IPCC (2019)
Typical NH_3 losses from liquid/slurry—without natural crust cover (poultry)	NH_3 loss	% of N_{ex}	40	-38	88	IPCC (2019)

Parameter	Variable	Data Input Unit	Estimated Value	Lower Uncertainty (%)	Upper Uncertainty (%)	Data Source
Typical NH_3 losses from liquid/slurry—with natural cover (other animals)	NH_3 loss	% of N_{ex}	15	—	—	IPCC (2019)
Typical NH_3 losses from liquid/slurry—with cover (swine, dairy cow, and other cattle)	NH_3 loss	% of N_{ex}	10	-70	20	IPCC (2019)
Typical NH_3 losses from liquid/slurry—with cover (poultry)	NH_3 loss	% of N_{ex}	8	-38	88	IPCC (2019)
Typical NH_3 losses from liquid/slurry—with cover (other animals)	NH_3 loss	% of N_{ex}	3	—	—	IPCC (2019)
Typical N leaching	N leaching loss	% of N_{ex}	0	—	—	IPCC (2019)

All default values have a triangular distribution.

Confidence intervals for emission factors and input variables for the activity data used for CH_4 leaking from digesters are listed in table 4B-13.

Table 4B-13. Uncertainty Data for CH_4 Leaking From Digesters

Parameter	Variable	Data Input Unit	Estimated Value	Lower Uncertainty (%)	Upper Uncertainty (%)
Digesters with steel or lined concrete or fiberglass digesters with a gas holding system (egg-shaped digesters) and monolithic construction	$EF_{CH4,leakage}$	%	2.8	- 100	100
UASB-type digesters with floating gas holders and no external water seal	$EF_{CH4,leakage}$	%	5	- 100	100
Digesters with unlined concrete/ ferrocement/brick masonry arched-type gas holding section; monolithic fixed-dome digesters	$EF_{CH4,leakage}$	%	10	- 100	100
Other digester configurations	$EF_{CH4,leakage}$	%	10	- 100	100

Uncertainty based on authors' expert opinion.

Appendix 4-C: Summary of Research and Data Gaps for Animal Production

This appendix discusses research gaps associated with animal production GHG emissions. The list is not exhaustive: it highlights key gaps, subjects that will need further research or development before there is enough information on them to be included in the methodology.

4-C.1 Enteric CH_4 Emissions From Ruminants

Better estimates of enteric CH_4 emissions from dairy cattle, beef cattle, sheep and goats would require:

- Better diet characterization data and improved estimation of nutrient excretion, at a national level, to move to a Tier 3 approach.
- Improved understanding of dietary and ruminal factors affecting enteric CH_4 production in all cattle, including finishing cattle. This fundamental research is needed as a basis for strategies to reduce emissions while not affecting animal health and well-being.
- A more thorough database of enteric CH_4 production of cattle grazing native range and other unimproved and improved pastures throughout the year.
- A more complete understanding of the effects of forage quality, forage intake, and supplementation strategies on all groups of cattle, particularly grazing cattle. Understanding the link between plant chemical composition and ruminal fermentation would make it possible to use information about strategic supplementation to reduce emissions.
- Continued refinement and development of CH_4 measurement techniques. There are more and more options for scientists and increasingly the methods can enable producers to use the data. More of these methods are going to be needed with carbon trading.

As well as more research in the following areas is needed to refine equations:

- Enteric CH_4 production of finishing and dairy cattle, considering dietary factors such as grain processing/starch availability. For ruminants that are fed grains, the form of that supplement can affect CH_4 emissions and animal performance and thus the models that are used for inventorying.
- Enteric CH_4 production of grazing cattle based on changes in forage quality and management throughout the year. Without this information, the models to predict emissions too fraught with large uncertainties to be useful.
- Methods to measure DMI measurements on pasture or range. These are the foundation of all models, but for many ruminants they are not particularly robust.
- A survey of diets and ingredients currently fed to ruminants. This would make certain that predictions of Y_m are valid and account for inhibitors currently fed.

4-C.2 Enteric CH_4 Emissions Mitigation

There is a need for enteric CH_4 inhibitors and mitigation strategies that are practical, safe, and effective in real-world situations. They must also be consumer-acceptable practices.

In addition, more research for the following is needed to bolster and refine the usability of the mitigation equations:

- Additive effects of using multiple mitigation strategies (e.g., 3-NOP and lipid supplementation). In particular, are the additive reductions cumulative or do factors such as hydrogen accumulation cause the mitigation practices to not meet the full reduction potential.
- The length of time that is both reasonable and physically possible to achieve the reduction potential. Timelines outside of the presented studies are unknown and factors such as rumen bacteria adaption would likely affect reduction potential over time.
- More research quantifying emission reductions from drugs or feed additives (for example, there are few studies on red algae).

4-C.3 Manure Storage and Treatment and Housing Emissions

The following information would improve the estimation of housing and manure storage and treatment emissions:

- Better equations to predict manure CH_4 and N_2O emissions that take into account dietary factors (nutrient composition, grain and forage processing, etc.) and their effects on the form and degradability of volatile solids (all volatile solids are not the same—starch vs. fiber, undigestible fiber, etc.) and excretion of nitrogen. As diets change, the ability to reflect these changes on GHG generation in housing and manure handling systems is essential to improve on-farm and inventory estimates.
- A national dataset evaluating the effects of dietary factors, climate, and manure handling systems on maximum CH_4 production potential (B_0) and MCFs. At present, data on B_0 are based on very limited and outdated information. In addition, there have been limited data available to determine MCF values across a range of manure types, climate, and storage characteristics. As all housing and manure storage estimates depend heavily on these factors, they are a research priority.
- Better N_2O emission factors for housing and manure management. Data quantifying the effects of diet, manure characteristics, and climate on N_2O emissions, over a range of housing and manure management systems, are very limited. More data are needed to improve these estimates to better quantify on-farm and national emissions.
- More research and updated methodologies to account for methane emissions from digestate from anaerobic digestion. Remaining volatile solids could vary greatly depending on the system and its operation. The maximum methane producing capacity of the digestate is also unknown; research is needed to determine these values.
- While IPCC (2019) offers guidance on indirect N_2O emissions estimates, the authors recognize the uncertainty surrounding this methodology and associated variables. The methods are recommended here to acknowledge that these emissions do occur and would have an impact on an entity's calculated emissions but note that the uncertainty of these estimates are higher and need further research and development. It is expected that future versions of these methods will refine these methodologies.
- Continued research and compilation (meta-analyses) on volatile solids and nitrogen removal from manure through solid-liquid separation. While some data exist, the range of removal is often large and therefore increases the uncertainty on provided default data. In addition, nitrogen removal was not added to this version of the report due to the preferred

methodology not indicating total nitrogen within the system. In addition, the VS loss after housing before additional manure storage and treatment is expected to be minor, though currently is not accounted in the methods (unlike losses to total nitrogen).

- The next version of the report should consider if emissions from belt poultry housing are captured completely within the current methodology. While there will be ammonia emissions, they will likely be less than normal roofed housing as is currently presented in the chapter.
- The emissions from housing and manure storage and treatment do not currently include bedding inputs. The addition of these inputs may be considered for future version of this report.

The following data would improve the estimation of manure management emissions, especially at a larger (e.g., regional or national) scale:

- Characterization of manure management systems in the United States. Reliable data describing the range of manure management systems in the United States, and the amount of manure stored in each system, are scarce. This severely hinders the ability to produce reliable emissions estimates at larger scales such as regions, States, and the entire country.

4-C.4 Uncertainty Data Gaps

While there are some known default values (see appendix 5-B), quantifying uncertainty as an implicit, explicit-model, or explicit-measurement based method, as discussed in chapter 8, requires more information than was available for this version of the report. To encourage transparency, USDA noted this gap within the chapter and hopes to prioritize this improvement in the next version of the report.

Appendix 4-D Background on Management Factors that Do Not Affect Y_m

This appendix discusses the background on management factors that do not affect Y_m, and subsequently were not included in the baseline scenario but that do affect lifetime GHG emissions of beef cattle. As noted in section 4.2.2, a modified IPCC (2006, 2019) Tier 2 method is proposed to estimate enteric CH_4 emissions from finishing beef cattle and established a baseline scenario using typical U.S. beef cattle feeding conditions and set baseline values using published research. To estimate CH_4 emissions, emission values are modified using adjustment factors based on changes in animal management and feeding conditions from the baseline scenario. Section 4.2.2.1 and appendix 4-B discuss the background information on the base diet and Y_m adjustment factors. This appendix summarizes several management and dietary factors not included in the Y_m adjustment factors for feedlot cattle that do not affect enteric CH_4 emissions but do potentially affect GHG production per unit of beef production.[2]

- **Beta-agonists:** Beta-agonists do not directly affect ruminal fermentation; therefore, no adjustment factor is recommended. Although Hales et al. (2017a) reported that the beta agonist zilpaterol hydrochloride (Zilmax, Merck & Co.) decreased enteric CH_4 emissions, possibly due to changes in ruminal rate of passage, Walter et al. (2016) noted no effect of zilpaterol on ruminal CH_4 production. However, because of a 4-percent increase in feed efficiency, a 2.5- to 3.5-percent increase in hot carcass weight and an increase in live body weight (Delmore et al., 2010; Elam et al., 2009; Montgomery et al., 2009; Radunz, 2011; Vasconcelos et al., 2008), enteric CH_4 emissions per unit of production are decreased when beta-agonists are fed.
- **Melengestrol acetate, or MGA (heifers only):** Feeding MGA (Zoetis, Parsippany, NJ) to heifers does not directly affect enteric CH_4 emissions. However, because of a 9-percent increase in the gain:feed ratio (Hill et al., 1988; Kreikemeier and Mader, 2004), enteric CH_4 emissions per unit of production decrease when heifers are fed MGA.
- **Direct Fed Microbials (DFM):** Most DFM do not appear to directly affect enteric CH_4 emissions, and the effects of DFM on animal performance are somewhat variable (Krehbiel et al., 2003). Therefore, no adjustment factor is recommended for the feeding of DFM.
- **Dietary CP and ruminal degradable protein (RDP):** Dietary CP may affect animal performance and enteric CH_4 emissions via effects on ruminal fermentation. However, there is no readily available data on modern feedlot diets with which to compare varying levels of CP and resulting CH_4 emissions (Berger and Merchen, 1995; Cole et al., 2006; Gleghorn et al., 2004; Jennings et al., 2018; Robinson and Okine, 2001; Wagner et al., 2010). Therefore, there is no recommended Y_m adjustment factor for dietary protein. However, dietary protein may affect emissions of manure management N_2O emissions and unquestionably affects NH_3 emissions (Todd et al., 2005; 2013).
- **Implanting regimens:** Growth-promoting implants do not directly affect enteric CH_4 emissions. However, because of an increase in feed efficiency, live body weight, and hot carcass weight (Herschler et al., 1995; Robinson and Okine, 2001; Wileman et al., 2009), enteric CH_4 emissions per unit of production decrease when implants are used.

[2] Hence, in evaluating CH_4 intensity per unit of production, these factors would have an impact.

- **Ambient temperature:** Cold and hot temperatures may affect enteric CH_4 emissions due to effects on feed intake, ruminal digestion, and rate of passage (Young, 1981); however, the actual effects are not clear. Therefore, no adjustment factor for environmental temperature is used. Cold temperatures may decrease CH_4, N_2O, and NH_3 losses from the pen surface.

Appendix 4-E: Feedstuffs Composition Table

Feedstuff	DM%	CP%	DE (mcal/kg)	GE (mcal/kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a] DE (% of GE)	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a] GE (mcal/kg)	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
Alfalfa *(Medicago sativa)*															
Fresh, late vegetative	21	20	2.78	3.763	2.7	9.8	*66.78*	63	67.5	4.185			38.9	29	7
Fresh, early bloom	23	19	2.65	3.763	3.1	9.5	*63.34*	60	68.4	4.204			40.1	36	7
Fresh, midbloom	24	18.3	2.56	3.763	2.6	8.7	*61.24*	58	70.4	4.200			46	35	9
Fresh, full bloom	25	14	2.43	3.763	2.8	8.5	*58.76*	55	74.7	4.154			52	37	10
Hay, sun-cured, early bloom	90	18	2.65	3.763	3	9.6	*63.72*	60	69.4	4.179			42	31	8
Hay, sun-cured, midbloom	90	17	2.56	3.763	2.6	9.1	*61.79*	58	71.3	4.164			46	35	9
Hay, sun-cured, late bloom	90	14	2.29	3.763	1.8	7.8	*55.71*	52	76.4	4.131			52	39	12
Hay, sun-cured, mature	91	12.9	2.21	3.763	1.3	7.5	*54.18*	50	78.3	4.101			58.8	44	14
Meal dehydrated, 17% protein	93.83	18.49	2.69	3.764	3.99	10.29	*64.18*	61	67.23	4.210	5.67	2.08	46.6	35.4	7.44
Silage wilted, early bloom	35	17	2.65		3.2	8.2	*62.85*	60	71.6	4.233			43	33	10
Silage wilted, midbloom	38	15.5	2.56		3.1	7.9	*60.93*	58	73.5	4.217			47	35	11
Silage wilted, full bloom	45	14	2.43		2.7	7.7	*58.34*	55	75.6	4.182			51	38	12
Alfalfa cubes	91.04	18.1	2.47		2.13	11.98	*61.65*	56	67.79	4.036		1.35	45.46	35.41	7.57
Almond *(Prunus amygdalus)*															
Hulls	89.21	5.47	2.61		2.8	8.29	*64.97*	55	83.44	4.035	15.05	2.5	38.96	32.73	11.06
Apple *(Malus spp.)*															
Pomace oat hulls added, dehydrated	89	5.1	2.47		5.2	3.5	*56.69*	56	86.2	4.354		3.98	45.56	38.72	14.85
Bahiagrass *(Paspalum notatum)*															
Fresh	30	8.9	2.38		1.6	11.1	*61.38*	54	78.4	3.907			68	38	7
Hay, sun-cured	91	8.2	2.25		2.1	6.4	*54.85*	51	83.3	4.118			72	41	8
Bakery															
Waste, dehydrated (dried bakery product)	88.86	13.14	3.13		10.04	4.08	*66.27*	89	72.74	4.705	11.2	34.03	14.98	7.87	2.59
Barley *Hordeum vulgare*															
Grain	89.69	12.78	3.71	4.332	2.2	2.77	*85.56*	84	82.25	4.342	10.65	56.74	18.29	7.09	1.75

							Calculated: Ewan, 1989[a]			Calculated: NASEM, 2016[a]					
Feedstuff	**DM%**	**CP%**	**DE (mcal/ kg)**	**GE (mcal/ kg)**	**EE (%)**	**Ash (%)**	**DE (% of GE)**	**TDN (%)**	**Total $(CH_2O)_n$ (%)**	**GE (mcal/kg)**	**Total Sugars (%)**	**Total Starch (%)**	**NDF (%)**	**ADF (%)**	**Lignin (%)**
Grain, Pacific coast	89	10.8	3.79		2	3.1	*88.54*	86	84.1	4.288			21	9	
Grain screenings	89	13.1	3.53		2.6	3.4	*81.42*	80	80.9	4.342					
Hay, sun-cured	87.99	10.95	2.65		2.41	8.36	*65.04*	56	78.28	4.094	10.31	5.66	56.88	33.88	4.32
Silage	33.63	12.05	2.67		3.47	8.65	*64.53*	51	75.83	4.154	5.53	9.17	54.77	34.73	4.77
Straw	85.07	6.08	1.76		1.9	7.1	*43.69*	40	84.92	4.046			71.63	50.09	5.16
Bean, navy *(Phaseolus vulgaris)*															
Seeds	89	25.3	3.7		1.5	5.2	*84.52*	84	68	4.392	7.03	29.27	17.77	11.96	1.8
Beet, mangel *(Beta vulgaris macrorrhiza)*															
Roots, fresh	11	11.8	3.53		0.7	9.6	*89.67*	80	77.9	3.965					
Beet, sugar *(Beta vulgaris altissima)*															
Aerial part with crowns, silage	22	13.4	2.25		2.8	32.5	*73.27*	51	51.3	3.149					
Pulp, dehydrated	91.49	9.07	2.94		1.14	6.84	*72.74*	74	82.95	4.062	8.55	0.93	41.33	26.35	3.94
Pulp, wet	21..95	9.55	2.94		0.86	8.59	*74.31*	72	81	3.982	23.21	1.65	48.23	28.06	4.37
Pulp with molasses, dehydrated	92	10.1	3.35		0.6	6.1	*82.52*	76	83.2	4.080			44	25	3
Bermudagrass *(Cynodon dactylon)*															
Fresh	34.94	15.16	2.53		2.76	8.63	*61.03*	60	73.45	4.164		1.79	66.6	36.14	5.03
Hay, sun-cured	92.99	11.11	2.48		1.86	7.94	*61.02*	46	79.09	4.085	5.8	4.78	66.98	35.65	5.41
Bermudagrass, coastal *(Cynodon dactylon)*															
Fresh	29	15	2.82		3.8	6.3	*65.53*	64	74.9	4.313					
Hay, sun-cured	90	6	2.16		2.3	6.6	*53.05*	49	85.1	4.087	5.83	3.98	66.2	35.2	5.18
Bluegrass, Canada *(Poa compressa)*															
Fresh, early vegetative	26	18.7	3.13		3.7	9.1	*73.99*	71	68.5	4.247					
Hay, sun-cured, late vegetative	97	0	2.12					48	100						
Bluegrass, Kentucky *(Poa pratensis)*															
Fresh, early vegetative	31	17.4	3.17		3.6	9.4	*75.62*	72	69.6	4.210			55	29	3
Fresh, mature	42	9.5	2.47		3.1	6.2	*59.00*	56	81.2	4.198			73.3	36.8	6
Hay, sun-cured	89	13	2.47		3.5	6.6	*58.21*	56	76.9	4.255			68.83	40.4	

Feedstuff	DM%	CP%	DE (mcal/ kg)	GE (mcal/ kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a]	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a]	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
							DE (% of GE)			GE (mcal/kg)					
Hay, sun-cured, full bloom	92	8.9	2.12		3.3	5.9	*50.46*	48	81.9	4.212					
Bluestem *(Andropagon spp.)*															
Fresh, early vegetative	27	12.8	3		2.8	8.9	*73.17*	68	75.5	4.120				43.51	
Fresh, mature	59	5.8	2.34		2.4	5.6	*56.82*	53	86.2	4.131					
Hay, sun-cured	89.19	6.02	2.21		1.35	9.7	*56.93*	50	82.93	3.909			69.71	43.32	
Brewers															
Grains, dehydrated	93.16	25.02	3.17	5.03	8.52	4.57	*66.12*	66	61.89	4.783	3.23	5.77	52.12	25.39	6.65
Grains, wet	25.96	28.52	3.26	5.03	9.51	4.38	*66.39*	66	57.59	4.895	0.5	4.81	49.99	24.32	6.74
Brome *(Bromus spp.)*															
Fresh, early vegetative	34	18	3.26		3.7	10.7	*78.57*	74	67.6	4.170			47.9	31	4
Hay, sun-cured, late vegetative	88	16	2.65		2.6	9.4	*64.40*	60	72	4.136	9.85	2.64	65.92	40.29	
Hay, sun-cured, late bloom	89	10	2.43		2.3	8.4	*59.97*	55	79.3	4.072			68	43	8
Brome, smooth *(Bromus inermis)*															
Fresh, early vegetative	30	21.3	3.22		4.2	10.1	*75.71*	73	64.4	4.271			47.9	31	4
Fresh, mature	55	6	2.34		2.4	6.9	*57.58*	53	84.7	4.080					
Hay, sun-cured, midbloom	90	14.6	2.47		2.6	10	*60.72*	56	72.8	4.091			57.7	36.8	4
Buckwheat, common *(Fagopyrum sagittatum)*															
Grain	88	12.5	3.17		2.8	2.3	*72.27*	72	82.4	4.389					
Buffalograss *(Buchloe dactyloides)*															
Fresh	46	10.3	2.47		1.9	12.4	*64.02*	56	75.4	3.890		5.49	74	36	6
Canarygrass, beed *(Phalaris arundinacea)*															
Fresh	27	11.6	2.65		3.5	8.3	*63.89*	60	76.6	4.163			46.4	28.3	4
Hay, sun-cured	91	10.3	2.43		3.1	7.9	*58.93*	55	78.7	4.139			70.5	36.6	4
Canola *(Brassica)*															
Grain	94.72	23.9	4.81		39.79	4.33	*73.56*	109.2	31.98	6.418		1.4	28.25	21.99	6.4
Canola meal	90.43	40.86	3.13		7.32	7.41	*64.67*	71.1	44.41	4.840	8.75	1.29	30.16	21.42	8.83

Feedstuff	DM%	CP%	DE (mcal/kg)	GE (mcal/kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a] DE (% of GE)	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a] GE (mcal/kg)	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
Carrot *(Daucus spp.)*															
Roots, fresh	12	9.9	3.7		1.4	8.2	*92.29*	84	80.5	4.032	19.09	2.09	23.78	19.94	2.72
Cassava, common *(Manihot esculenta)*															
Tubers, meal	88	2.6	3.75		0.8	3.3	*91.88*	85	93.3	4.094					
Tubers, fresh	37	3.6	3.53		1	3.9	*86.49*	80	91.5	4.095					
Cereals															
Grain screenings	90	13.4	3		4.1	6	*69.61*	68	76.5	4.317					
Grain screenings refuse	91	14.1	2.65		4.9	9.8	*63.13*	60	71.2	4.212					
Grain screenings, uncleaned	92	15.1	2.87		5.9	9.3	*66.89*	65	69.7	4.300					
Citrus *(Citrus spp.)*															
Pulp, silage	21	7.3	3.88		9.7	5.5	*85.21*	88	77.5	4.541					
Pulp without fines, dehydrated (dried citrus pulp)	91	6.7	3.62		3.7	6.6	*87.01*	82	83	4.171	19.47	1	24.02	20.43	2.45
Citrus pulp, wet	19.41	8.58	3.1		3.17	6.78	*74.68*	70.2	81.47	4.164	0.9	1.7	26.29	23.16	3.21
Clover, alsike *(Trifolium hybridum)*															
Fresh, early vegetative	19	24.1	2.91		3.2	12.8	*70.62*	66	59.9	4.148					
Hay, sun-cured	88	14.9	2.56		3	8.7	*61.66*	58	73.4	4.170					
Clover, crimson *(Trifolium incarnatum)*															
Fresh, early vegetative	18	17	2.78					63	83	4.405					
Hay, sun-cured	87	18.4	2.51		2.4	11	*61.68*	57	68.2	4.096					
Clover, ladino *(Trifolium repens)*															
Fresh, early vegetative	19	27.2	3	4.64	2.5	13.5	*73.22*	68	56.8	4.129			35	33	
Hay, sun-cured	90	22	2.65	4.64	2.7	10.1	*63.40*	60	65.2	4.203			36	32	7
Clover, red *(Trifolium pratense)*															
Fresh, early bloom	20	19.4	3.04		5	10.2	*71.27*	69	65.4	4.280			40	31	
Fresh, full bloom	26	14.6	2.82		2.9	7.8	*67.44*	64	74.7	4.198			43	35	
Fresh, regrowth early vegetative	18	21	3					68	79	4.465					
Hay, sun-cured	89	16	2.43		2.8	8.5	*58.33*	55	72.7	4.184			46.9	36	10

							Calculated: Ewan, 1989[a]			Calculated: NASEM, 2016[a]					
Feedstuff	**DM%**	**CP%**	**DE (mcal/ kg)**	**GE (mcal/ kg)**	**EE (%)**	**Ash (%)**	**DE (% of GE)**	**TDN (%)**	**Total $(CH_2O)_n$ (%)**	**GE (mcal/kg)**	**Total Sugars (%)**	**Total Starch (%)**	**NDF (%)**	**ADF (%)**	**Lignin (%)**
Coconut *(Cocos nucifera)*															
Kernels with coats, meal mechanical extracted (copra meal)	92	22.4	3.62		6.9	7.3	*79.66*	82	63.4	4.545					
Kernels with coats, meal solvent extracted (copra meal)	91	23.4	3.31		3.9	6.6	*74.85*	75	66.1	4.432	7.88	0.73	52.26	32.23	10.34
Corn, dent yellow *(Zea mays indentata)*															
Aerial part with ears, sun-cured (fodder)	81	8.9	2.87		2.4	6.8	*69.80*	65	81.9	4.127			55	33	3
Aerial part with ears, sun-cured, mature (fodder)	82	8	3.04		2.3	5.4	*73.18*	69	84.3	4.167	4.26	32.58	43	25.46	3.17
Aerial part without ears, without husks, sun-cured (stover) (straw)	85	6.6	2.21		1.3	7.2	*55.28*	50	84.9	4.018			67	39	11
Cobs, ground	90	3.2	2.21		0.7	1.7	*53.18*	50	94.4	4.164	3.75	14.34	78.26	42.03	4.05
Distillers grains, dehydrated	94	23	3.79		9.8	2.4	*76.86*	86	64.8	4.910			43		
Distillers grains with solubles, dehydrated	92	25	3.88		10.3	4.8	*79.45*	88	59.9	4.867	1.16	5.88	33.66	16.17	4.96
Distillers solubles, dehydrated	93	29.7	3.88		9.2	7.8	*81.50*	88	53.3	4.755			23	7	1
Distillers grains with solubles, wet (corn-based)	31.44	30.63	4.32		10.84	5.13	*86.68*	98	53.4	4.966	0.9	6.06	31.52	15.27	4.7
Ears, ground (corn and cob meal)	87	9	3.66		3.7	1.9	*83.15*	83	85.4	4.400					
Ears with husks, silage	44	8.9	3.26		3.8	2.8	*74.67*	74	84.5	4.367	1.29	60.16	21.04	9.89	1.74
Gluten, meal	91	46.8	3.79		2.4	3.4	*78.47*	86	47.4	4.837					
Gluten, meal 60% protein	90	67.2	3.92		2.4	1.8	*75.29*	89	28.6	5.209	0.23	15.42	8.07	4.81	2.26
Gluten with bran (corn gluten feed)	90	25.6	3.66	4.73	2.4	7.5	*84.50*	83	64.5	4.349	3.4	15.23	38.53	11.78	1.6
Grain, grade 2, 69.5 kg/hl	88	10.1	3.97	4.5445	4.2	1.4	*88.85*	90	84.3	4.464	2.72	69.7	9.95	3.72	1.15
Grain, flaked	86	11.2	4.19		2.2	1	*95.44*	95	85.6	4.392	2.48	76.24	8.97	3.59	1.25
Grain, high moisture	72	10.7	4.1		4.3	1.6	*91.64*	93	83.4	4.470	2.16	71.3	9.86	3.69	1.15
Grits, by-products (hominy feed)	90	11.5	4.14	4.693	7.7	3.1	*89.80*	94	77.7	4.598	1.1	56.77	16.79	5.62	1.48
Silage, aerial part without ears, without husks (stalklage) (stover)	31	6.3	2.43		2.1	11.6	*63.20*	55	80	3.873			68	55	7
Silage, few ears	29	8.4	2.73		3	7.2	*66.26*	62	81.4	4.135					

Feedstuff	DM%	CP%	DE (mcal/ kg)	GE (mcal/ kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a]	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a]	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
							DE (% of GE)			GE (mcal/kg)					
Silage, well-eared	33	8.1	3.09		3.1	4.5	*72.88*	70	84.3	4.248	4.26	32.58	42.98	25.46	3.17
Corn snaplage	58.94	8.08	3.61		3.46	1.99	*82.60*	82	86.47	4.370		57.02	23.28	11.24	1.95
Corn stalkage	40.74	6.81	2.36		1.99	12.15	*61.75*	53.6	79.05	3.852		5.98	63.78	45.61	6.12
Corn gluten feed (sweet bran)	60.07	23.76	3.92		4.65	6.4	*87.54*	89	65.19	4.485			26.75	9.79	
Corn gluten feed, wet	43.76	21.7	3.79		4.29	6.4	*85.61*	86	67.61	4.435	3.4	15.23	38.53	11.78	1.6
Corn gluten feed, dry	88.92	22.64	3.53		3.32	6.4	*80.47*	80	67.64	4.398	2.68	16.92	35.05	11.18	1.86
Corn germ meal	90.59	22.14	3.46		11.5	4.31	*70.19*	78.6	62.05	4.907		19.68	39.41	12.27	2.44
Corn stalks	85.81	6.07	2.32		1.44	11.1	*60.63*	52.7	81.39	3.856	3.1	10.8	70.83	46.75	6.31
Corn grain, dry-rolled	87.22	8.79	3.86		3.81	1.44	*87.23*	87.6	85.96	4.422	1.81	72.07	9.72	3.56	1.18
Corn steep liquor	46.41	31.78	4.32	.	4.51	11.29	*98.73*	98	52.42	4.395	15.03	11.4	3.55	2.72	.
Hominy feed	88.74	10.27	3.85		7.15	2.64	*84.04*	87.2	79.94	4.570	1.1	56.77	16.79	5.62	1.48
Corn, sweet *(Zea mays saccharate)*															
Process residue, fresh (cannery residue)	77	8.8	3.09		2.3	3.3	*72.56*	70	85.6	4.266					
Process residue, silage (cannery residue)	32	7.7	3.17		5.2	4.9	*73.14*	72	82.2	4.335					
Cotton *(Gossypium spp.)*															
Bolls, sun-cured	92	11	1.94		2.7	7.7	*47.08*	44	78.6	4.137					
Hulls	91.43	6.68	1.85		2.71	3.62	*43.68*	42	86.99	4.242	1.13	2.71	81.07	65.1	19.29
Seeds	92.63	22.87	4.23		19.45	4.12	*78.42*	96	53.56	5.343	3.96	2.2	47.82	42.85	11.58
Seeds, meal mechanical extracted, 41% protein	93	44.3	3.44	4.78	5	6.6	*71.71*	78	44.1	4.803			28	20	6
Seeds, meal prepressed extracted, 41% protein	91	45.6	3.53	4.692	1.3	7	*76.88*	80	46.1	4.612			26	19	6
Seeds, meal solvent extracted, 41% protein	91	45.2	3.35	4.705	1.6	7.1	*72.85*	76	46.1	4.617	1.7	3.93	33.6	23.67	8.51
Seeds without hulls, meal prepressed solvent extracted 50% protein	93	54	3.31		1.4	7.1	*70.14*	75	37.5	4.739					
Cotton burrs	90.55	8.66	1.99		2.48	15.34	*53.25*	45.2	73.52	3.773	2.7	6.03	60.9	55.93	16.6
Cotton gin trash	90.87	12.29	2.14		3.64	12.05	*53.49*	48.5	72.02	4.025		1.06	60.57	52.26	15.85

Feedstuff	DM%	CP%	DE (mcal/kg)	GE (mcal/kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a] DE (% of GE)	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a] GE (mcal/kg)	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
Cowpea, common *(Vigna sinensis)*															
Hay, sun-cured	90	19.4	2.6		3.1	11.3	*63.25*	59	66.2	4.135					
Dropseed, sand *(Sporobolus cryptandrus)*															
Fresh, stem-cured	88	5	2.6		1.4	6.3	*64.69*	59	87.3	4.037					6
Fats and oils															
Fat, animal, dehydrated	99	0	7.8		99.5	0	*80.29*	177	0.5	9.374	0	0	0	0	0
Fat, animal-poultry	99	0	7.8		100	0	*80.06*	177	0	9.400	0	0	0	0	0
Oil, vegetable	100	0	7.8	9.396	99.9	0	*80.10*	177	0.1	9.395	0	0	0	0	0
Fescue *(Festuca spp.)*															
Hay, sun-cured, early vegetative	91	12.4	2.69		3.4	12	*67.39*	61	72.2	4.017			57	32	3
Hay, sun-cured, early bloom	92	9.5	2.12		2	10	*53.57*	48	78.5	3.983			72	39	5
Fish															
Fish meal	92.3	66.24	3.61		11.89	20.02	*73.35*	81.9	1.85	4.937		5.82	13.6	3.14	
Flax, common *(Linum usitatissimum)*															
Seed screenings	91	18.2	2.82		10.2	6.8	*60.15*	64	64.8	4.676					
Seeds, meal mechanical extracted, linseed meal	91	37.9	3.62		6	6.3	*75.89*	82	49.8	4.772			25	17	7
Seeds, meal solvent extracted, linseed meal	90	38.3	3.44		1.5	6.5	*76.18*	78	53.7	4.534			25	19	6
Flax seed, whole	91.63	28.68	3.6		27.67	5.12	*61.04*	81.6	38.53	5.820		1.98	31.84	18.94	5.75
Galeta *(Hilaria jamesii)*															
Fresh, stem-cured	71	5.5	2.12		1.8	16.2	*58.67*	48	76.5	3.655					
Glycerin	80.25	0.84	3.04		6.24	6.69	*72.20*	69	86.23	4.213	1.4	0.4	0.3	0.2	
Grama *(Bouteloua spp.)*															
Fresh, early vegetative	41	13.1	2.65		2	11.3	*67.02*	60	73.6	3.983					
Fresh, mature	63	6.5	2.43		1.7	11.4	*63.38*	55	80.4	3.864					

Feedstuff	DM%	CP%	DE (mcal/ kg)	GE (mcal/ kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a] DE (% of GE)	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a] GE (mcal/kg)	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
Grape *(Vitis spp.)*															
Marc, dehydrated (pomace)	91.81	12.27	2.07		8.87	9.65	*47.05*	27	69.21	4.399		0.97	51.78	46.28	31.91
Mark, wet (pomace)	41.88	11.69	2.47		8.95	15.11	*59.45*	28	64.25	4.168		0.99	50.06	43.43	27.6
Hemicellulose extract (masonex)	76	0.7	2.65		0.4	4.1	*66.32*	60	94.8	4.011					
Lespedeza, common, and lespedeza, Korean *(Lespedeza striata)*															
Fresh, late vegetative	32	16.4	2.6					59	83.6	4.396					
Fresh, early bloom	28	16.4	2.43					55	83.6	4.396					
Hay, sun-cured, early bloom	93	15.5	2.43					55	84.5	4.383					
Hay, sun-cured, midbloom	93	14.5	2.21					50	85.5	4.368					
Hay, sun-cured, full bloom	93	13.4	2.07					47	86.6	4.351					
Lignin sulfonate, calcium															
Dehydrated	97	0.5	0.35		0.5	4	*8.74*	8	95	4.018					76
Linseed *(Linum)*															
Linseed meal	90.47	36.93	3.24		11.96	6.18	*63.59*	73.6	44.93	5.075		2.54	32.1	17.28	5.72
Meadow plants, intermountain															
Hay, sun-cured	95	8.7	2.56		2.5	8.5	*63.37*	58	80.3	4.059	13.95		60.85	35.79	
Millet, foxtail *(Setaria italica)*															
Fresh	28	9.5	2.78		3.1	8.7	*68.20*	63	78.7	4.094	7.89	2.69	65.28	34.53	7.13
Grain	86.7	11.27	3.36		3.46	5.34	*78.67*	85	79.93	4.279	3.7	49.27	21.61	13.88	3.21
Hay, sun-cured	87	8.6	2.6		2.9	8.6	*64.10*	59	79.9	4.074	5.64	3.15	60.3	42.03	5.73
Millet, proso *(Panicum miliaceum)*															
Grain	90	12.9	3.7		3.9	2.9	*83.57*	84	80.3	4.428	3.7	45.45	23.16	14.54	3.8
Molasses and syrup *(Beta vulgaris altissima)*															
Beet, sugar, molasses, more than 48% invert sugar, more than 79.5% degrees brix	78	8.5	3.48		0.2	11.3	*91.95*	79	80	3.819	35.5	0.6	0.77	0.36	0.16

Feedstuff	DM%	CP%	DE (mcal/kg)	GE (mcal/kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a] DE (% of GE)	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a] GE (mcal/kg)	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
Molasses and syrup *(Citrus spp.)*															
Citrus, syrup (citrus molasses)	68	8.2	3.31		0.3	7.9	*84.11*	75	83.6	3.961					
Molasses and syrup *(Saccharum officinarum)*															
Sugarcane, molasses, dehydrated	94	10.3	3.09		0.9	13.3	*82.12*	70	75.5	3.800					
Sugarcane, molasses, more than 46% invert sugars, more than 79.5 degrees brix (black strap)	66.04	8.59	3.17		1.86	12.2	*82.57*	72	77.35	3.870	60.04	11.98			
Napiergrass *(Pennisetum purpureum)*															
Fresh, late vegetative	20	8.7	2.43		3	8.6	*59.81*	55	79.7	4.081			70	45	10
Fresh, late bloom	23	7.8	2.34		1.1	5.3	*57.24*	53	85.8	4.105			75	47	14
Needleandthread *(Stipa comata)*															
Fresh, stem-cured	92	4.1	2.16		5.4	21.1	*60.36*	49	69.4	3.619			83	43	14
Oats *(Avena sativa)*															
Grain	89.96	13.3	3.4	4.667	5.4	3.4	*75.63*	77	77.9	4.492	2.18	44.09	26.65	13.3	3
Grain, Pacific coast	91	10	3.44		5.5	4.2	*77.90*	78	80.3	4.414					
Groats	90	17.7	4.14		6.9	2.4	*88.29*	94	73	4.678					
Hay, sun-cured	89.61	8.73	2.64		2.22	7.07	*64.59*	55	81.98	4.104	10.9	3.97	59.13	37.08	4.69
Hulls	91.6	6.1	2.49		2.8	5.24	*59.85*	35	85.86	4.171	3.03	15.83	64.44	35.87	5.54
Silage, late vegetative	23	12.8	2.87		2.5	6.5	*68.51*	65	78.2	4.204	5.08	3.11	58.88	38.49	5.33
Silage, dough stage	35	10	2.51		4.1	6.9	*59.49*	57	79	4.229					
Straw	84.19	4.83	1.98		1.33	6.92	*49.68*	45	86.92	4.005		1.35	73.75	49.29	7.07
Orchardgrass *(Dactylis glomerata)*															
Fresh, early vegetative	23	18.4	3.17		4.9	11.3	*75.54*	72	65.4	4.214			58.1	30.7	
Fresh, midbloom	31	11	2.51		3.5	7.5	*60.13*	57	78	4.188			57.6	35.6	
Hay, sun-cured, early bloom	89	15	2.87		2.8	8.7	*69.29*	65	73.5	4.161			59.6	33.8	
Hay, sun-cured, late bloom	91.47	13.77	2.38		2.3	10.54	*59.28*	54	73.39	4.040			65	37.8	

Feedstuff	DM%	CP%	DE (mcal/kg)	GE (mcal/kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a] DE (% of GE)	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a] GE (mcal/kg)	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
Pangolagrass *(Digitaria decumbens)*															
Fresh	21	10.3	2.43		2.3	9.6	*60.69*	55	77.8	4.027				38	5
Hay, sun-cured, 15 to 28 days growth	91	11.5	2.25		2.2	8.5	*55.35*	51	77.8	4.085			70	41	6
Hay, sun-cured, 29 to 42 days growth	91	7.1	1.98		2	8	*49.38*	45	82.9	4.030			73	43	6
Hay, sun-cured, 43 to 56 days growth	91	5.5	1.76		2	7.6	*43.97*	40	84.9	4.022			77	46	7
Pea *(Pisum spp.)*															
Seeds	89	25.3	3.84		1.4	3.3	*86.18*	87	70	4.466		42.66	13.67	9.23	1.06
Straw	87	8.9	2.03		1.8	6.5	*49.62*	46	82.8	4.108					
Vines without seeds, silage	25	13.1	2.51		3.3	9	*60.80*	57	74.6	4.146		5.58	59	49	9
Field peas	89.9	14.8	2.6		1.9	8	*63.12*	59	75.3	4.140		46.3	13.1	7.16	
Peanut *(Arachis hypogaea)*															
Hay, sun-cured	91	10.8	2.43		3.4	8.6	*59.02*	55	77.2	4.134	7.42	4	47.4	39.13	8.45
Hulls (pods)	91	7.8	0.97		2	4.2	*23.17*	22	86	4.198	6.52	1.24	68.46	58.87	23.03
Kernels, meal mechanical extracted (peanut meal)	93	52	3.66		6.3	5.5	*72.71*	83	36.2	5.033	9.96	6.93	19.89	13.15	3.3
Kernels, meal solvent extracted (peanut meal)	92	52.3	3.4		1.4	6.3	*71.90*	77	40	4.747					
Pearlmillet *(Pennisetum glaucum)*															
Fresh	21	8.5	2.69		2.2	10	*68.04*	61	79.3	3.978					
Pineapple *(Ananas comosus)*															
Aerial part without fruit, sun-cured (pineapple hay)	89	7.8	2.69		2.8	6.1	*64.84*	61	83.3	4.161					
Process residue, dehydrated (pineapple bran)	87	4.6	3		1.5	3.5	*72.43*	68	90.4	4.153			73	37	7
Potato *(Solanum tuberosum)*															
Process residue, dehydrated	89	8.4	3.97		4	3.4	*91.40*	90	84.2	4.345	3.7	44.34	18.38	13.31	3.2
Tubers, fresh	23.54	10.11	3.38		7.52	6.3	*76.15*	81	76.07	4.435	11.91	60.87	11.19	7.32	1.1
Tubers, silage	25	7.6	3.62		4	5.5	*85.40*	82	82.9	4.246					

Feedstuff	DM%	CP%	DE (mcal/kg)	GE (mcal/kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a]	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a]	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
							DE (% of GE)			GE (mcal/kg)					
Poultry															
Feathers, hydrolyzed	93	91.3	3.09		3.2	3.8	*55.93*	70	1.7	5.530					
Prairie plants, Midwest															
Hay, sun-cured	92	5.8	2.25		2.4	7.1	*55.53*	51	84.7	4.068			66.58	41.45	2.05
Rape *(Brassica napus)* (Canola)															
Fresh, early bloom	11	23.5	3.31		3.8	14	*80.88*	75	58.7	4.121					
Seeds, meal mechanical extracted	92	38.7	3.35		7.9	7.5	*69.27*	76	45.9	4.834					
Seeds, meal solvent extracted	91	40.6	3.04		1.8	7.5	*67.21*	69	50.1	4.542	8.75	1.29	30.16	21.42	8.83
Redtop *(Agrostis alba)*															
Fresh	29	11.6	2.78		3.9	8.1	*66.52*	63	76.4	4.193			64	45	8
Hay, sun-cured, midbloom	94	11.7	2.51		2.6	6.5	*60.08*	57	79.2	4.192					
Rice *(Oryza sativa)*															
Bran with germs (rice, bran)	91	14.1	3.09		15.1	12.8	*66.64*	70	58	4.623	6.33	20.17	26.22	15.51	5.34
Grain, ground (ground rough rice)	88.81	8.37	3.65		1.84	3.19	*86.26*	79	86.6	4.240	3.35	57.19	16.17	5.9	1.88
Hulls	91.95	5.39	31.5		4.31	15.71	*834.66*	12	74.59	3.805			53.84	52.55	.
Straw	91	4.3	1.81		1.4	17	*51.16*	41	77.3	3.583			82	49	16
Rye *(Secale cereale)*															
Distillers grains, dehydrated	92	23.5	2.69		7.8	2.5	*55.78*	61	66.2	4.808					
Fresh	24	15.9	3.04		3.7	8.1	*71.83*	69	72.3	4.247					
Grain	88	13.8	3.7		1.7	1.9	*84.83*	84	82.6	4.367		58.25	15.39	7.53	1.57
Mill run, less than 9.5% fiber (rye feed)	90	18.5	3.31		3.7	4.2	*74.50*	75	73.6	4.447					
Straw	90	3	1.37		1.7	5	*33.72*	31	90.3	4.077					
Ryegrass, Italian *(Lolium multiflorum)*															
Fresh	25	14.5	2.65	4.5	3.2	14	*67.54*	60	68.3	3.955					
Hay, sun-cured, late vegetative	90.38	18.65	2.81	4.5	3.35	9.6	*67.10*	62	68.4	4.207		2.26	51.5	30.89	4.32
Hay, sun-cured, early bloom	83	5.5	2.38	4.5	0.9	8.4	*60.93*	54	85.2	3.931					

Feedstuff	DM%	CP%	DE (mcal/kg)	GE (mcal/kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a]	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a]	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
							DE (% of GE)			GE (mcal/kg)					
Ryegrass, Perennial *(Lolium perenne)*															
Fresh	27	10.4	3	4.5	2.7	8.6	*73.68*	68	78.3	4.091					
Hay, sun-cured	86	8.6	2.65	4.5	2.2	11.5	*68.14*	60	77.7	3.917			41	30	2
Safflower *(Carthamus tinctorious)*															
Seeds	94	17.4	3.92		35.1	3.1	*62.89*	89	44.4	6.125					
Seeds, meal mechanical extracted	91	22.1	2.65		6.7	4.1	*56.75*	60	67.1	4.663			59	41	
Seeds, meal solvent extracted	93.5	23.12	2.46		12.34	4.85	*49.52*	57	59.69	4.943	3.96	1.15	51.48	37.62	13.45
Seeds without hulls, meal solvent extracted	92	46.9	3.22		1.4	8.2	*70.55*	73	43.5	4.587					
Sage, black *(Salvia mellifera)*															
Browse, fresh, stem-cured	65	8.5	2.16		10.8	5.5	*46.62*	49	75.2	4.616			42	30	12
Sagebrush, big *(Artemisia tridentata)*															
Browse, fresh, stem-cured	65	9.3	2.21		11	6.6	*47.96*	50	73.1	4.593					
Sagebrush, bud *(Artemisia spinescens)*															
Browse, fresh, early vegetative	23	17.3	2.25		4.9	21.4	*60.24*	51	56.4	3.779					
Browse, fresh, late vegetative	32	17.5	2.29		2.5	21.6	*63.70*	52	58.4	3.647					
Sagebrush, fringed *(Artemisia frigida)*															
Browse, fresh, midbloom	43	9.4	2.56		2	6.5	*62.29*	58	82.1	4.126					
Browse, fresh, mature	60	7.1	2.25		3.4	17.1	*61.02*	51	72.4	3.725			46	35	10
Saltbush, nuttall *(Atriplex nuttallii)*															
Browse, fresh, stem-cured	55	7.2	1.59		2.2	21.5	*46.38*	36	69.1	3.481					
Saltgrass *(Distichlis spp.)*															
Fresh, post ripe	74	4.2	2.34		2.6	7.3	*58.06*	53	85.9	4.047					
Hay, sun-cured	89	8.9	2.25		2.1	12.7	*58.67*	51	76.3	3.867					
Seaweed, kelp *(Laminariales fucales)*															
Whole, dehydrated	91	7.1	1.41		0.5	38.6	*54.67*	32	53.8	2.681					

Feedstuff	DM%	CP%	DE (mcal/kg)	GE (mcal/kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a]	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a]	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
							DE (% of GE)			GE (mcal/kg)					
Sedge *(Carex spp.)*															
Hay, sun-cured	89	9.4	2.29		2.4	7.2	*55.83*	52	81	4.118					
Sesame *(Sesamum indicum)*															
Seeds, meal mechanical extracted	93	49.1	3.4		7.5	12.1	*71.32*	77	31.3	4.778			17	17	2
Solka Floc	93	0	3.09					70	100	4.150			99	79	4
Sorghum *(Sorghum bicolor)*															
Aerial part with heads, sun-cured (fodder)	89	7.5	2.56		2.4	9.4	*64.38*	58	80.7	3.998					
Aerial part without heads, sun-cured (stover)	88	5.2	2.38		1.7	11	*62.11*	54	82.1	3.861		7.33	56.44	36.49	2.9
Distillers grains, dehydrated	94	34.4	3.66		9.5	3.8	*72.85*	83	52.3	5.007					
Distillers grains with solubles, wet (sorghum-based)	31.4	34.4	3.66		11.25	3.8	*71.46*	83	50.55	5.099			37	27.6	
Grain, less than 8% protein	88	7.7	3.75	4.405	3			85	89.3	4.423					
Grain, 8% to 10% protein	87	10.1	3.7		3.4	2.1	*84.23*	84	84.4	4.393					
Grain, more than 10% protein	88.7	11.64	3.79		3.5	2.09	*85.71*	83	82.77	4.422	0.1	71.16	7.2	4.57	1.15
Grain, flaked	85	10.19	4.06		2.4	2.1	*93.59475*	92	85.31	4.342		75.18	9.7	6.26	
Grain, reconstituted	70	10.19	4.1		2.4	2.1	*94.51687*	93	85.31	4.342		72.89	9.28	5.52	
Silage	30	7.5	2.65		3	8.7	*65.58*	60	80.8	4.059	0.19	4.63	49.17	31.08	5.64
Sorghum, johnsongrass *(Sorghum halepense)*															
Hay, sun-cured	89	9.5	2.34		2.4	8.2	*57.65*	53	79.9	4.078					
Sorghum, sorgo *(Sorghum bicolor saccharatum)*															
Silage	27	6.2	2.56		2.6	6.4	*62.44*	58	84.8	4.114	1.44	9.79	57.71	37.02	5.34
Sorghum, sudangrass *(Sorghum bicolor sudanense)*															
Fresh, early vegetative	18	16.8	3.09		3.9	9	*73.27*	70	70.3	4.233	8.16	2.08	61.02	37.35	4.74
Fresh, midbloom	23	8.8	2.78		1.8	10.5	*71.03*	63	78.9	3.941			65	40	5
Hay, sun-cured	91	8	2.47		1.8	9.6	*62.67*	56	80.6	3.966	7.07	1.42	65.7	41.6	5.06
Silage	28	10.8	2.43		2.8	9.8	*60.29*	55	76.6	4.052	4.5	3.12	61.14	39.65	5.47

Feedstuff	DM%	CP%	DE (mcal/ kg)	GE (mcal/ kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a]	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a]	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
							DE (% of GE)			GE (mcal/kg)					
Soybean *(Glycine max)*															
Hay, sun-cured, midbloom	90.5	16.54	2.65		3.04	8.79	*63.48*	53	71.63	4.193	4.9	5.37	44.85	37.05	7.28
Hulls (seed coats)	90.04	12.37	2.76		2.28	5.05	*65.19*	64	80.3	4.246	2.15	1.1	64.81	46.4	2.47
Seeds	92	42.8	4.01		18.8	5.5	*71.66*	91	32.9	5.551		1.03	17.98	10.75	1.92
Seeds, meal mechanical extracted	90	47.7	3.75	4.708	5.3	6.7	*77.15*	85	40.3	4.866					
Seeds, meal solvent extracted, 44% protein	91.68	46.53	3.58	4.708	8.34	6.43	*71.24*	84	38.7	5.019	11.55	5.05	18.78	10.93	1.48
Seeds without hulls, meal solvent extracted	89.24	52.85	3.51	4.708	1.88	7.36	*74.41*	87	37.91	4.736	13.3	2.02	11.33	7.48	1.17
Silage	37.35	17.08	2.55		4.29	9.81	*60.60*	55	68.82	4.224		4.21	47.53	36.86	8.01
Straw	88	5.2	1.85		1.5	6.4	*45.98*	42	86.9	4.041			70	54	16
Spelt *(Triticum spelta)*															
Grain	90	13.3	3.31		2.1	3.9	*77.18*	75	80.7	4.298					
Squirreltail *(Stanion spp.)*															
Fresh, stem-cured	50	3.1	2.21		2.2	17	*62.00*	50	77.7	3.607					
Sugarcane *(saccharum officinarum)*															
Bagasse, dehydrated	91	1.6	2.12		0.7	3.2	*52.15*	48	94.5	4.078		0.87	75.58	62.11	17.31
Stems, fresh	15	7.6	2.69		0.7	6	*66.71*	61	85.7	4.052	12.33	1.08	74	44	11
Sugar	100	0	4.32		0	0		98	100	4.150	100	0	0	0	0
Summercypress, gray *(Kochia vestita)*															
Fresh, stem-cured	85	9	2.21		3.7	24.8	*65.11*	50	62.5	3.450					
Sunflower, common *(Helianthus annuus)*															
Seeds, meal solvent extracted	90.44	35.01	2.93		10.8	6.41	*58.71*	44	47.78	4.976	6.6	1	40.51	29.46	9.12
Seeds without hulls, meal mechanical extracted	93	44.6	3.26		8.7	7.1	*65.37*	74	39.6	4.981					
Seeds without hulls, meal solvent extracted	93	49.8	2.87		3.1	8.1	*60.97*	65	39	4.724		1.07	41.71	30.34	9.04
Sweetclover, yellow *(Melilotus officinalis)*															
Hay, sun-cured	87	15.7	2.38		2	8.8	*58.00*	54	73.5	4.125					

Feedstuff	DM%	CP%	DE (mcal/kg)	GE (mcal/kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a]	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a]	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
							DE (% of GE)			GE (mcal/kg)					
Timothy *(Phleum pratense)*															
Fresh, late vegetative	26	18	3.17		3.8	6.6	*73.12*	72	71.6	4.346			55.7	29	
Fresh, midbloom	29	9.1	2.78		3	6.6	*66.87*	63	81.3	4.170			64	37	4
Hay, sun-cured, late vegetative	89	17	2.73		2.8	7.1	*64.35*	62	73.1	4.257			55	29	3
Hay, sun-cured, early bloom	90	15	2.6		2.9	5.7	*60.75*	59	76.4	4.291			61.4	35.2	4
Hay, sun-cured, midbloom	87.8	9.44	2.51		1.93	8.5	*62.46*	57	80.13	4.040	14.15		63.81	38.04	5
Hay, sun-cured, full bloom	89	8.1	2.47		3.1	5.2	*58.68*	56	83.6	4.218			68	38	6
Silage, full bloom	36	9.7	2.47		3.2	6.9	*59.32*	56	80.2	4.177			64.2	37.5	
Tomato *(Lycopersicon esculentum)*															
Pomace, dehydrated	92	23.5	2.56		10.3	7.5	*53.98*	58	58.7	4.732	13.98	1	43.86	37.2	15.78
Trefoil, birdsfoot *(Lotus corniculatus)*															
Fresh	24	21	2.91		2.7	9	*69.07*	66	67.3	4.233			46.7		
Hay, sun-cured	92	16.3	2.6		2.5	7	*61.62*	59	74.2	4.235			47.5	36	9
Triticale *(Triticale hexaploide)*															
Grain	88.84	12.13	3.65		1.65	1.96	*84.27*	84	84.26	4.337	2.9	61.04	14.1	4.49	1.81
Triticale hay	91.3	11	2.58		2.11	8.39	*63.59*	58.5	78.5	4.078	8.45	2.64	58.57	37.98	4.82
Turnip *(Brassica rapa rapa)*															
Roots, fresh	9	11.8	3.75		1.9	8.9	*92.94*	85	77.4	4.057			44	34	0
Urea															
45% nitrogen, 281% protein equivalent	99	287	0	0	0	0	*0*	0	0	0.000	0	0	0	0	0
Vetch *(Vicia spp.)*															
hay, sun-cured	89	20.8	2.51		3	9.1	*59.44*	57	67.1	4.242			48	33	8
Wheat *(Triticum aestivum)*															
Bran	90.1	17.48	3.17		4.32	5.48	*71.95*	70	72.72	4.412	5.32	21.17	40.09	13.72	4.15
Bread, dehydrated	95	13	3.79		2.4	2.4	*86.79*	86	82.2	4.371					
Flour by-product, less than 7% fiber (wheat shorts)	88	18.6	3.22		5.2	4.9	*71.59*	73	71.3	4.499		25.56	38.33	13.23	3.66

Feedstuff	DM%	CP%	DE (mcal/ kg)	GE (mcal/ kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a] DE (% of GE)	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a] GE (mcal/kg)	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
Flour by-product, less than 9.5% fiber (wheat middlings)	89	18.4	3.04	4.553	4.9	5.2	*68.09*	69	71.5	4.467			35.9	11.7	
Fresh, early vegetative	34.11	15.32	61.7		3	8.91	*1487.19*	73	72.77	4.168	10.5	4.11	54.16	32.99	3.87
Grain	89	16	3.88	4.434	2	1.9	*87.95*	88	80.1	4.416	8.55	62.42	12.36	4.15	1.52
Grain, hard red spring	88	17.2	3.92		2	1.8	*88.41*	89	79	4.438					
Grain, hard winter	88	14.4	3.88		1.8	1.9	*88.66*	88	81.9	4.382					
Grain, soft red winter	88	13	3.92		1.8	2.1	*90.19*	89	83.1	4.352					
Grain, soft white winter	89	11.3	3.92		1.9	1.8	*90.33*	89	85	4.345			14	4	
Grain, soft white winter, pacific coast	89	11.2	3.88		2.2	2.1	*89.36*	88	84.5	4.346					
Grain screenings	89	15.8	3.13		3.9	6.1	*72.29*	71	74.2	4.339	4.23	34.22	30.41	17.76	5.07
Grain, steam flaked	82.96	14.42	3.82		1.88	1.97	*87.26*	86.8	81.73	4.383		64.89	13.55	5.51	
Hay, sun-cured	88	8.5	2.56		2.2	7.1	*62.73*	58	82.2	4.098	9.35	4.68	57.89	35.89	4.82
Mill run, less than 9.5% fiber (midds)	90	17.2	3.48		4.6	5.9	*79.11*	79	72.3	4.405	5.13	23.03	37.38	13.2	3.74
Silage, full bloom	25	8.1	2.6		3	8.4	*63.99*	59	80.5	4.080	1.81	6.62	56.54	36.59	4.77
Straw	89	3.6	1.81		1.8	7.8	*45.77*	41	86.8	3.975	2.5	1.64	73.65	50.23	7.42
Wheat, durum *(Triticum durum)*															
Grain	88	15.9	3.75		2	1.8	*84.95*	85	80.3	4.419					
Wheatgrass, crested *(Agropyron desertorum)*															
Fresh, early vegetative	28	21.5	3.31		2.2	10	*79.78*	75	66.3	4.173					
Fresh, full bloom	45	9.8	2.69		3.6	9.3	*65.89*	61	77.3	4.100					
Fresh, post ripe	80	3.1	2.16		1.2	4.1	*52.99*	49	91.6	4.089					
Hay, sun-cured	95	12.4	2.34		2.3	7.2	*56.51*	53	78.1	4.158					
Whey *(Bos taurus)*															
Dehydrated (cattle)	93	14.2	3.57	3.905	0.7	9.8	*90.06*	81	75.3	3.993	56.09	1.28	0.55	0.4	0.1
Fresh (cattle)	7	13	4.14		4.3	8.7	*98.67*	94	74	4.210	50.6	3.28	1.66	4.23	0.6
Low lactose, dehydrated (dried whey product) (cattle)	93	17.9	3.48		1.1	16.5	*92.87*	79	64.5	3.792					

Feedstuff	DM%	CP%	DE (mcal/kg)	GE (mcal/kg)	EE (%)	Ash (%)	Calculated: Ewan, 1989[a] DE (% of GE)	TDN (%)	Total $(CH_2O)_n$ (%)	Calculated: NASEM, 2016[a] GE (mcal/kg)	Total Sugars (%)	Total Starch (%)	NDF (%)	ADF (%)	Lignin (%)
Winterfat, common *(Eurotia lanata)*															
Fresh, stem-cured	80	10.8	1.54		2.8	15.8	*40.89*	35	70.6	3.803			72	44	10
Yeast, brewers *(Saccharomyces cerevisiae)*															
Dehydrated	93	46.9	3.48		0.9	7.1	*75.91*	79	45.1	4.606	9.42	8.87	7.56	4.38	1.4
Yeast, irradiated *(Saccharomyces cerevisiae)*															
Dehydrated	94	51.2	3.35		1.2	6.6	*71.46*	76	41	4.707					
Yeast, primary *(Saccharomyces cerevisiae)*															
Dehydrated	93	51.8	3.4		1.1	8.6	*73.86*	77	38.5	4.628					
Yeast, torula *(Torulopsis utilis)*															
Dehydrated	93	52.7	3.44		1.7	8.3	*73.76*	78	37.3	4.685					

Sources: Ewan, 1989; NASEM, 2016; Dairy One, 2021.

[a] Calculations for feedstuffs composition table are presented below:

Calculations For Feedstuffs Composition Table

Calculated gross energy from Ewan (1989):

$$GE = [4143 + (56 \times EE\%) + (15 \times CP\%) - (44 \times Ash)] \div 1{,}000$$

Calculated total carbohydrates $(CH_2O)_n$ from NASEM (2016):

$$Carb = CP\% - EE\% - Ash$$

Calculated gross energy from NASEM (2016):

$$GE = [(5.65 \times CP\%) + (9.4 \times EE\%) + (4.15 \times Carb)] \div 100$$

Where:

GE	=	calculated gross energy (mcal/kg)
$EE\%$	=	percent ether extract
$CP\%$	=	percent crude protein
Ash	=	percent ash
$Carb$	=	percent total carbohydrates $(CH_2O)_n$

Appendix 4-F: IPCC (2019) Equations

Equation 4-11 and equation 4-14 within chapter 4 require several calculated values to calculate gross energy. The following equations and tables are provided as published in IPCC (2019) guidelines for convenience to the users of this report. Equation 4-12 may require reference to IPCC (2019) Table 10.12.

IPCC (2019) Equation 10.3: Net Energy for Maintenance

$$NE_m = Cf_i \times (Weight)^{0.75}$$

Where:

NE_m	=	net energy required by the animal for maintenance (MJ/day)
Cf_i	=	a coefficient which varies for each animal category as shown in table 10.4 (MJ/day/kg)
Weight	=	live weight of animal (kg)

IPCC (2019) Table 10.4. (Updated) Coefficients for Calculating Net Energy for Maintenance (NE_m)

Animal Category	Cf_i (MJ/day/kg)	Comments
Cattle/Buffalo	0.322	All nonlactating cows, steers, heifers, and calves
Cattle/Buffalo (lactating cows)	0.386	Maintenance energy requirements are 20% higher during lactation
Cattle/Buffalo (bulls)	0.370	Maintenance energy requirements are 15% higher for intact males than nonlactating females
Sheep (lamb to 1 year)	0.236	This value can be increased by 15% for intact males.
Sheep (older than 1 year)	0.217	This value can be increased by 15% for intact males.
Goats	0.315	

IPCC (2019) Equation 10.4: Net Energy for Activity (for Cattle and Buffalo)

$$NE_a = C_a \times NE_m$$

Where:

NE_a	=	net energy for animal activity (MJ/day)
C_a	=	coefficient corresponding to animal's feeding situation (table 10.5) (MJ/day/kg)
NE_m	=	net energy required by the animal for maintenance (MJ/day)

IPCC (2019) Equation 10.5: Net Energy for Activity (for Sheep and Goats)

$$NE_a = C_a \times (Weight)$$

Where:

NE_a	=	net energy for animal activity (MJ/day)
C_a	=	coefficient corresponding to animal's feeding situation (table 10.5) (MJ/day/kg)
Weight	=	live weight of animal (kg)

IPCC (2019) Table 10.5. (Updated) Activity Coefficients Corresponding to Animal's Feeding Situation

Situation	Definition	C_a
Cattle and Buffalo (unit for C_a is dimensionless)		
Stall	Animals are confined to a small area (i.e., tethered, pen, barn) with the result that they expend very little or no energy to acquire feed.	0
Pasture	Animals are confined in areas with sufficient forage requiring modest energy expense to acquire feed	0.17
Grazing large areas	Animals graze in open ranged land or hilly terrain and expend significant energy to acquired feed.	0.36
Sheep and goats (unit for C_a= MJ/day/kg)		
Housed ewes	Animals are confined due to pregnancy in final trimester (50 days).	0.0096
Grazing flat pasture	Animals walk up to 1,000 meters per day and expend very little energy to acquire feed.	0.0107
Grazing hilly pasture	Animals walk up to 5,000 meters per day and expend significant energy to acquire feed.	0.024
Housed fattening lambs	Animals are housed for fattening.	0.0067
Lowland goats	Animals walk and graze in lowland pasture.	0.019
Hill and mountain goats	Animals graze in open range land or hilly terrain and expend significant energy to acquire feed.	0.024

IPCC (2019) Equation 10.6: Net Energy for Growth (For Cattle and Buffalo)

$$NE_g = 22.02 \times \left(\frac{BW}{C \times MW}\right)^{0.75} \times WG^{1.097}$$

Where:

NE_g = net energy needed for growth (MJ/day)

BW = the average live body weight of the animals in the population (kg)

C = a coefficient with a value of 0.8 for females, 1.0 for castrates and 1.2 for bulls (NRC 1996)

MW = the mature body weight of an adult animal individually, mature females, mature males and steer in moderate body condition (kg)

WG = the average daily weight gain of the animals in the population (kg/day)

IPCC (2019) Equation 10.7: Net Energy for Growth (For Sheep and Goats) (Updated)

$$NE_g = \frac{WG_{lamb/kid} \times \left(a + 0.5b\left(BW_i + BW_f\right)\right)}{365}$$

Where:

NE_g	=	net energy needed for growth (MJ/day)
$WG_{lamb/kid}$	=	the weight gain (BW_f—BW_i) (kg/year)
BW_i	=	the live body weight at weaning (kg)
BW_f	=	the live body weight at 1-year old or at slaughter (live weight) if slaughtered prior to 1 year of age (kg)
a, b	=	constants from table 10.6

IPCC (2019) Table 10.6. (Updated) Constants for Use in Calculating NE_G for Sheep and Goats

Animal species/category	a (MG/kg)	b (MG/kg)
Intact males (Sheep)	2.5	0.35
Castrates (Sheep)	4.4	0.32
Females (Sheep)	2.1	0.45
Goats (All categories)	5.0	0.33

Source: Cited within IPCC (2019) as AFRC (1993; 1995).

IPCC (2019) Equation 10.8: Net Energy for Lactation (Beef Cattle, Dairy Cattle and Buffalo)

$$NE_l = Milk \times (1.47 + 0.40 \times Fat)$$

Where:

NE_l	=	net energy for lactation (MJ/day)
$Milk$	=	amount of milk produced (kg of milk/day)
Fat	=	fat content of milk (% by weight)

IPCC (2019) Equation 10.9: (Updated) Net Energy for Lactation for Sheep and Goats (Milk Production Known)

$$NE_l = Milk \times EV_{milk}$$

Where:

NE_l	=	net energy for lactation (MJ/day)
$Milk$	=	amount of milk produced (kg of milk/day)
EV_{milk}	=	net energy required to produce 1 kg of milk

IPCC (2019) Equation 10.10: Net Energy for Lactation for Sheep and Goats (Milk Production Unknown)

$$NE_l = \left[\frac{(5 \times WG_{wean})}{365}\right] \times EV_{milk}$$

Where:

NE_l	=	net energy for lactation (MJ/day)
WG_{wean}	=	the weight gain of the lamb between birth and weaning (kg)
EV_{milk}	=	the energy required to produce 1 kg of milk (MJ/kg)

A default EV_{milk} value of 4.6 MJ/kg (sheep) (AFRC 1993; AFRC 1995) and 3 MJ/kg (goats) (AFRC 1998) can be used which corresponds to a milk fat content of 7% and 3.8% by weight for sheep and goats, respectively. Milk fat can vary greatly among breeds.

IPCC (2019) Equation 10.11: Net Energy for Work (for Cattle and Buffalo)

$$NE_{work} = 0.10 \times NE_m \times Hours$$

Where:

NE_{work}	=	net energy for work (MJ/day)
NE_m	=	net energy required by the animal for maintenance (equation 10.3) (MJ/day)
$Hours$	=	number of hours of work/day

IPCC (2019) Equation 10.12: (Updated) Net Energy to Produce Wool (For Sheep and Goats)

$$NE_{wool} = \left(\frac{EV_{milk} \times Pr_{wool}}{365}\right)$$

Where:

NE_{wool}	=	net energy required to produce wool (MJ/day)
EV_{milk}	=	the energy value of each kg of wool produced (weighed after drying but before scouring) (MJ/kg). A default value of 24 MJ/kg can be used for sheep estimate. For goats this energy value is not considered unless fiber-producing goat numbers are relevant for a country (AFRC 1995).
Pr_{wool}	=	annual wool production per sheep/goat (kg/year)

IPCC (2019) Equation 10.13: Net Energy for Pregnancy (for Cattle/Buffalo and Sheep and Goats)

$$NE_p = C_{pregnancy} \times NE_m$$

Where:

NE_p	=	net energy required for pregnancy (MJ/day)
$C_{pregnancy}$	=	pregnancy coefficient (0.10 for Cattle and Buffalo, from table 10.7)
NE_m	=	net energy required by the animal for maintenance (equation 10.3), (MJ/day)

IPCC (2019) Table 10.7. (Updated) Constants for Use in Calculating NE_P in Equation 10.13

Animal Category	$C_{pregnancy}$
Cattle and Buffalo	0.10
Sheep/Goats	
Single Birth	0.077
Double birth (twins)	0.126
Triple birth or more (triplets)	0.150

IPCC (2019) Equation 10.14: Ratio of Net Energy Available in a Diet for Maintenance to Digestible Energy

$$REM = \left[1.123 - (0.004092 \times DE) + (0.00001126 \times (DE)^2) - \left(\frac{25.4}{DE}\right)\right]$$

Where:

REM = ratio of net energy available in diet for maintenance to digestible energy

DE = digestibility of feed expressed as a fraction of gross energy (digestible energy/gross energy)

IPCC (2019) Equation 10.15: Ratio of Net Energy Available for Growth in a Diet to Digestible Energy Consumed

$$REG = \left[1.164 - (0.00516 \times DE) + (0.00001308 \times (DE)^2) - \left(\frac{37.4}{DE}\right)\right]$$

Where:

REG = ratio of net energy available for growth in a diet to digestible energy consumed

DE = digestibility of feed expressed as a fraction of gross energy (digestible energy/gross energy)

IPCC (2019) Equation 10.16: Gross Energy for Cattle/Buffalo, Sheep and Goats

$$GE = \left[\frac{\left(\frac{NE_m + NE_a + NE_l + NE_{work} + NE_p}{REM}\right) + \left(\frac{NE_g + NE_{wool}}{REG}\right)}{DE} \right]$$

Where:

GE	=	gross energy (MJ/day)
NE_m	=	net energy required by the animal for maintenance (equation 10.3) (MJ/day)
NE_a	=	net energy for animal activity (equation 10.4 and equation 10.5) (MJ/day)
NE_l	=	net energy for lactation (equation 10.8 for cattle, equation 10.9 or equation 10.10 for sheep and goats) (MJ/day)
NE_{work}	=	net energy for work (equation 10.11) (MJ/day)
NE_p	=	net energy required for pregnancy (equation 10.13) (MJ/day)
REM	=	ratio of net energy available in a diet for maintenance to digestible energy (equation 10.14)
NE_g	=	net energy needed for growth (equation 10.6 for cattle, equation 10.7 for sheep and goats) (MJ/day)
REG	=	ratio of net energy available for growth in a diet to digestible energy consumed (equation 10.15)
NE_{wool}	=	net energy required to produce a year of wool (equation 10.12) (MJ/day)
DE	=	digestibility of feed expressed as a fraction of gross energy) digestible energy/gross energy)

IPCC (2019) Table 10.12. (Updated) Cattle/Buffalo Methane Conversion Factors (Y_m)

Livestock Category	Description	Feed Quality Digestibility (DE, %) and Neutral Detergent Fiber (NDF, %DMI)	MY, g CH_4/kg DMI	Y_m
Dairy cows and buffalo	High-producing cows (> 8500 kg/head/year)	DE ≥ 70 NDF ≤ 35	19.0	5.7
		DE ≥ 70 NDF ≥ 35	20.0	6.0
	Medium-producing cows (5000 -8500 kg/head/year)	DE 63-70 NDF > 37	21.0	6.3
	Low-producing cows (< 5000 kg/head/year)	DE ≤ 62 NDF > 38	21.4	6.5
Nondairy and multipurpose cattle and buffalo	> 75% forage	DE ≤ 62	23.3	7.0
	Rations of >75% high quality forage and/or mixed rations, forage of between 15 and 75% the total ration mixed with grain, and/or silage.	DE 62-71	21.0	6.3
	Feedlot (all other grains, 0–15% forage)	DE ≥ 72	13.6	4.0
	Feedlot (steam-flaked corn ionophore supplement, 0–10% forage)	DE > 75	10.0	3.0

Chapter 5 Quantifying Greenhouse Gas Sources and Sinks in Managed Forest Systems

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Acronyms, Chemical Formulae, and Units

AFOLU	agriculture, forestry, and other land use
ATLAS	Aggregate Timberland Assessment
C	carbon
CBM-CFS3	Carbon Budget Model of the Canadian Forest Sector
CCF	hundred cubic feet
CCT	Carbon Calculation Tool
CH_4	methane
cm	centimeter
CO	carbon monoxide
CO_2	carbon dioxide
CO_2-eq	carbon dioxide equivalents
COLE	Carbon OnLine Estimator
dbh	diameter at breast height
DDW	down dead wood (otherwise termed downed woody material)
DF	displacement factor
FFE	Fire and Fuels Extension
FIA	Forest Inventory and Analysis
FIADB	Forest Inventory and Analysis Database
FOFEM	First Order Fire Effects Model
FORCARB2	FORest CARBon Budget Model
FOROM	Forest Resource Outlook Model
FVS	Forest Vegetation Simulator
g	gram
GHG	greenhouse gas
GIS	geographic information system
GPS	Global Positioning System
GWP	global warming potential
ha	hectare
hp	horsepower
HWP	harvested wood product
IPCC	Intergovernmental Panel on Climate Change
ISO	International Organization for Standardization
kg	kilogram
LCA	life cycle assessment
LEARN	Land Emissions and Removals Navigator
m	meter
MBF	thousand board feet
Mg	megagram (metric ton or 1,000,000 grams)
MRV Toolkit	Measurement Reporting and Verification Toolkit
Mt	million metric tons
N_2O	nitrous oxide
NSVB	national scale volume and biomass
PEF	pollutant emission factor
RPA	Resources Planning Act
SOC	soil organic carbon

SQL	structured query language
SUNY	State University of New York
SWDS	solid waste disposal sites
Tg	teragram (million metric tons or 1,000,000,000,000 grams)
UNFCCC	United Nations Framework Convention on Climate Change
USDA	U.S. Department of Agriculture
U.S. EPA	U.S. Environmental Protection Agency
VOC	volatile organic compound
WARM	Waste Reduction Model

5. Quantifying Greenhouse Gas Sources and Sinks in Managed Forest Systems

This chapter provides methodologies and guidance on estimating greenhouse gas (GHG) emissions or carbon removals (i.e., sequestration) associated with entity-level activities of the forestry sector:

- Section 5.1 provides an overview of management practices and resulting GHG emissions or carbon removals, including silviculture practices and treatments, harvested wood products (HWPs), urban forest management, and wildfire and prescribed fire.[1] It also discusses system boundaries and temporal scale, the selected methods/models, and sources of data.
- Section 5.2 provides the methods for estimating carbon stocks and carbon stock change from managed forest systems. Note that—because forest operations are often integrated and planned over more space and time than other operations covered in this guidance—many entity-scale GHG estimations will need to use a number of these methods.

This chapter has three appendixes, as well as an accompanying Excel workbook:

- Appendix 5-A provides an overview of silvicultural practices, HWPs, urban forest management, and natural disturbances, including a general background for forestry management activities and details on how to use online tools.
- Appendix 5-B provides the rationale and technical documentation for the chosen methods.
- Appendix 5-C summarizes the known research gaps that inform these chosen methods as well as provides the basis for future development of methods.

The Excel workbook facilitates quantification approaches for silvicultural practices and improved forest management (section 5.2.1), HWPs (section 5.2.2), and wildfire and prescribed fire activities (section 5.2.3). It provides the resulting GHG estimations or carbon removals with user-defined inputs. These results are divided along sector boundaries to better agree with Intergovernmental Panel on Climate Change (IPCC) guidance. See table 5-5, in section 5.1, for a brief guide to the Excel workbook's structure.

5.1 Overview

The chapter is designed to be accessible to a diversity of users with a wide range of technical capacities and data availability. It also recognizes the continuum of specific goals for forest management activities meant to enhance carbon stocks or lower emissions.

5.1.1 Description of Sector

Forests are the largest terrestrial carbon sink in the world, taking in carbon dioxide (CO_2) and storing it as carbon in soils and woody plants (Pan et al., 2011) and HWP. In the United States, forests, urban trees, and wood products collectively offset total annual CO_2 emissions by 10–15 percent (USDA Forest Service, 2021), although this varies by State and region. In the 2021 annual GHG inventory reported by the U.S. Department of Agriculture (USDA) and the U.S. Environmental Protection Agency (EPA), forests sequestered a net total 593 million metric tons (Mt) of CO_2 per year on 281 million hectares (ha) of forest land, making this the main land category sequestering

[1] In this chapter, the terms "prescribed burn" and "prescribed fire" are applied synonymously when referring to fire that is intentionally ignited to meet management objectives.

carbon. Urban trees in settlement areas sequestered an additional net 138 Mt. A further 103 Mt CO_2 (new product storage and emissions) were added in 2021 to the pool of carbon stored in wood products. Collectively this represents an annual net 760 Mt of carbon dioxide equivalents (CO_2-eq) sequestered in 2021 (Domke et al., 2023).

These estimates have remained relatively consistent over the past two decades, despite increases in forest disturbances such as pests and wildfire, continued encroachment of settlements on forest areas, and demand for wood products (Oswalt et al., 2019). There are some indications that without additional investments in forests (both forest areas and settlement tree cover) these annual additions to the stored carbon pool will decline toward net-zero sequestration in the forest sector as available land becomes limited for afforestation, more land converts to development, and climate-induced disturbances reduce existing carbon stocks (Domke and Murray, 2021; Oswalt et al., 2019).

Forest management activities can substantially influence the amount of carbon stored in a forest, as well as what is available for use as wood products or bioenergy. The specific operations involved also affect the size of the carbon benefit that can be gained. Although operations such as tree harvesting, planting, fertilization, and trucking also produce GHG emissions from the fossil fuel used to carry out these activities (Ingerson, 2011), such emissions are not the focus of this chapter.

A range of forestry activities can be considered in projects that attempt to store atmospheric CO_2 as carbon in wood or avoid anticipated emissions. These include establishing new forests, planting trees on agricultural or urban land (i.e., agroforestry or urban arboriculture), avoiding forest clearing, avoiding wildfire emissions, and a range of silvicultural treatments/practices such as extended rotation lengths and uneven-aged silvicultural systems that enhance carbon stocks in managed forests and/or increase the resilience of these stocks to future global climate change effects. Forest management may be very effective at increasing the rate of biomass accumulation in commercial tree species. (See table 5A-2 in appendix 5-A for an extended list of the range of forest management activities among commercial even-aged plantations.) Forestry activities can also have effects on forest soils, woody debris, and the amount of carbon in wood products. These interventions often result in both emissions and removals of carbon.

Key concepts where harvesting occurs include:

- Climate benefits from harvesting under any rotation scenario have a much higher likelihood of realization if the carbon contained in the harvested stand is transferred into wood products. The exception may be in cases where it can be demonstrated that harvesting is effective in avoiding future emissions from disturbances such as fire, drought, and pests. In these cases, utilizing harvested biomass as wood products can increase the climate benefit.
- Where harvests are undertaken, postharvest land use is an important factor. Long-term climate benefits have a higher probability of achievement if harvests are responsibly conducted (e.g., maintain soil health and ensure tree regeneration) and postharvest land use continues as forest (through either natural regeneration or active planting of seedlings).

5.1.2 Resulting GHG Emissions

Through photosynthesis, green vegetation pulls CO_2 from the atmosphere, separates the carbon, and releases oxygen. Some of that carbon is returned to the atmosphere as $CO_2$when the plant uses carbon to produce energy while a large proportion is stored in plant tissues. This plant tissue, otherwise known as biomass, stores the carbon until its dead matter decomposes or combustion releases it as CO_2 to the atmosphere.

The carbon stock in forests increases when the amount of carbon withdrawn from the atmosphere through the growth of trees and plants (including lateral transfer to other pools such as dead wood) exceeds the release of carbon to the atmosphere. This is called "net sequestration" or "net carbon removal." U.S. forests as a whole have been in this state for over 100 years as they regrew in extent and size following extensive land clearing in the 1800s (Birdsey et al., 2006).

Forests may also become sources of CO_2 when disturbances, whether natural or human-caused, exceed the amount of growth in the forest. During and after these events—such as outbreaks of insects or disease, hurricanes, droughts, and wildfires or timber harvest—the rate of carbon emissions exceeds sequestration and net GHGs are added to the atmosphere.

CO_2 is always included in estimates of GHG flux from forest management activities. When forest ecosystems exchange other GHGs with relatively higher global warming potential (GWP), such as nitrous oxide (N_2O) and methane (CH_4), those gases are especially important to include if possible (see table 5-1). (See chapter 2 for more information on GWP.)

Table 5-1. GHGs Associated With Forest Management Activities

GHG	Driver of Flux in Forest Ecosystems	Associated Forest Management Activity
CO_2	Photosynthesis and decay/combustion of biomass.	All
N_2O	▪ Emitted from soils under wet conditions or after nitrogen fertilization. ▪ Released when biomass is burned.	▪ Emissions from fertilizer application ▪ Wildfire/prescribed fire
CH_4	▪ Often absorbed by the microbial community in forest soils but may also be emitted by wetland forest soils. ▪ Emitted when biomass is burned, particularly smoldering combustion of large-diameter woody fuels and ground fuels (Sommers et al., 2014).	Wildfire/prescribed fire

5.1.3 Carbon Pools

Carbon makes up about 50 percent of the dry weight of forest vegetation, also known as "biomass" (IPCC, 2006), though that proportion can vary depending on species and ecosystem type (Doraisami et al., 2022). Forest carbon accounting therefore primarily relies on estimating how much biomass and organic matter from biomass is in the system, including wood products. Forest biomass is delineated into discrete "carbon pools" (see figure 5-1 and table 5-2).

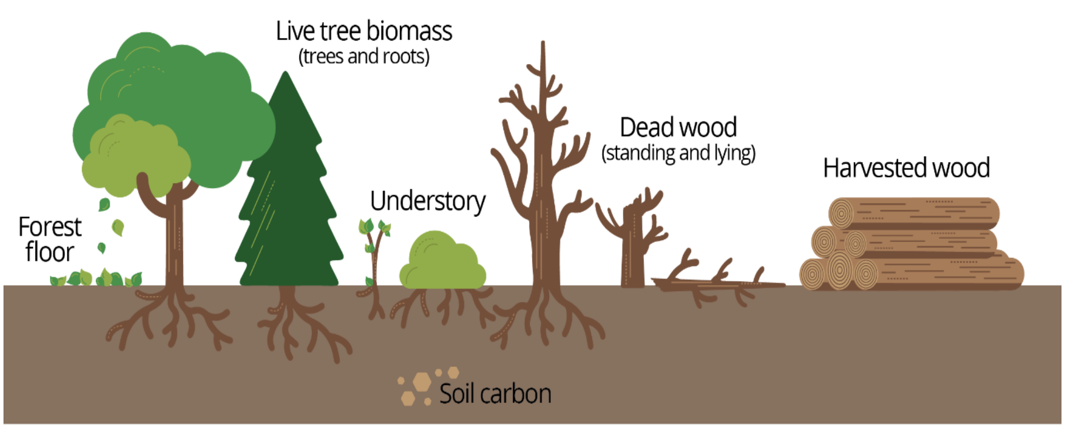


Figure 5-1. Forest Carbon Pools

Box 5-1. Land-Use Change vs. Land-Cover Change

The terms “land use” and “land cover” are often confused or used interchangeably, but there is an important distinction in the context of forest carbon accounting dynamics.

Land cover: The observed biophysical cover on the earth’s surface (Di Gregorio and Jansen, 2005). In the forestry context, forest land cover may decrease over a monitoring period as a result of disturbances like fire, disease, and harvest (Nelson et al., 2020). This tree cover loss does not equal deforestation because trees will often regrow after those disturbances. For example, forest management practices and harvest cycles often result in temporary land cover changes. Whether through replanting or natural regeneration, the forest cover returns over time.

Land use: The human-designated purpose or intent of the land regardless of the vegetative cover. Changes in land use reflect a more permanent transition to another ecosystem type. “Deforestation” specifically refers to instances where the land use (and often land cover) is permanently changed, i.e., where land transitions from forest to another land use. In the United States, the largest driver of land-use change is development for commercial and residential purposes (Nelson et al., 2020).

Carbon pools can be grouped in several different ways. This guidance uses a standard set of carbon pool definitions—those applied in the Forest Inventory and Analysis (FIA) program’s national inventory—that correspond to available lookup tables (Smith et al., 2006; Hoover et al., 2021). However, definitions and boundaries around pools can vary according to specific carbon estimation procedures/capabilities and reporting needs.

The biomass in these pools is generally not measured directly (i.e., through forest biomass sampling for laboratory determination of carbon content); instead, it is estimated indirectly using measurements from standard forest inventories and modeled associations.

It is best practice to identify the pools that will be accounted for at the beginning of the quantification effort. All relevant pools should be included, unless it can be shown that a pool would not have stock losses or emissions or anticipated carbon stock changes can be considered negligible or *de minimis* (see box 5-2).

Table 5-2. Summary of Carbon Pools

Forest Carbon Pools	Description
Live trees	Large woody perennial plants, capable of reaching at least 15 feet (4.6 meters) in height, with a diameter at breast height (dbh) or at root collar (if multi-stemmed woodland species) greater than 1 inch (2.5 centimeters). Includes the carbon mass in roots (i.e., live belowground biomass) with diameters greater than 0.08 inches (2 millimeters), stems, branches, and foliage. The per-tree carbon estimates are a function of tree species, diameter, height, and volume of wood. Trees less than 5 inches (12.7 centimeters) dbh are often sampled differently than those that are 5 inches (12.7 centimeters) or more.
Understory	Biomass of undergrowth plants in a forest, including woody shrubs and trees less than 1 inch (2.5 centimeters) dbh. Generally, a minor component of biomass or the live plant component.

Forest Carbon Pools	Description
Standing dead	Dead trees of at least 1 inch (2.5 centimeters) dbh—including carbon mass of coarse roots, stems, and branches—that have not yet fallen and do not lean more than 45 degrees from vertical (Burrill et al., 2021).[a] Includes coarse nonliving roots more than 0.08 inches (2 millimeters) in diameter.
Down dead wood (DDW), also known as coarse woody debris	All nonliving woody biomass with a diameter of at least 3 inches (7.6 centimeters) at transect intersection, lying on the ground. This pool also includes: ▪ Debris piles, usually from past logging ▪ Previously standing dead trees that have lost enough height or volume or lean more than 45 degrees from vertical so they do not qualify as standing dead ▪ Stumps with coarse roots (as previously defined) ▪ Nonliving vegetation that otherwise would fall under the definition of "understory" ▪ Coarse roots associated with fallen trees
Forest floor	The litter, fulvic, and humic layers, and all fine woody debris with a diameter less than 3 inches (7.6 centimeters) at transect intersection, lying on the ground above the mineral soil.
Forest soil organic carbon (SOC)	All organic material in soil to a depth of generally 3.3 feet (1 meter), including the fine roots—e.g., roots less than 0.08 inches (2 millimeters) in diameter—of the live and standing dead tree pools, but excluding the coarse roots of the aboveground and belowground live and dead biomass.
Products in use	Wood removed from the forest ecosystem and processed into products, not including logging debris (slash) left in the forest after harvesting.
HWPs in solid waste disposal sites (SWDS)	Wood products discarded into SWDS. Most of the carbon from long-lived or solid wood products remains stored for time periods exceeding a century, whereas most paper products are subject to decay over much shorter periods.

[a] The minimum diameter of standing dead trees may be increased (5 inches, or 12.7 centimeters, dbh) to accommodate past sampling protocols for estimation of change.

Box 5-2. The *De Minimis* Assumption

It is best practice to include all pools in efforts to quantify GHG flux from forest management activities, unless one can show that a pool's stock changes are small and do not significantly contribute to the total carbon stocks, or that a pool would not have stock losses or emissions. This is called the *de minimis* assumption, made when the change in the pool in question makes up an insignificant proportion of the total anticipated change in forest-related emissions within the accounting period. For this guidance, the *de minimis* threshold is 10 percent. For instance, in a reforestation activity where it may be difficult, time-consuming, or costly to estimate soil carbon change, and the soil carbon change is assumed to be *de minimis* in magnitude, it may be omitted from the quantification of total flux. Or, if it can be demonstrated that the soil pool will be accumulating carbon, the landowner may choose not to count that pool and thus be conservative about (i.e., underestimate) the sequestration potential of the project. This is an example of balancing principles of completeness and cost-effectiveness. Generally speaking, nontree vegetation is not a significant biomass component in mature forests, and the deadwood pool is typically not a significant part of carbon stocks in reforestation; the stock changes associated with such pools therefore could be considered *de minimis* (Pearson et al., 2005).

Products in use and products in solid waste disposal system pools are included in the forest carbon pool because they enable complete accounting of carbon as it cycles through creation to emission: captured in forest biomass through photosynthesis → potentially harvested → burned or decaying at various rates (depending on the biomass's fate), with some of the carbon ultimately returning to the atmosphere, but much of it stored indefinitely in landfills. IPCC defines these stages as forest carbon, carbon stored in products in use, and carbon stored in HWPs in solid waste disposal sites (SWDS) (such as landfills).

Table 5-3 provides considerations around including particular pools and GHGs in quantifying GHG flux from forest management activities.

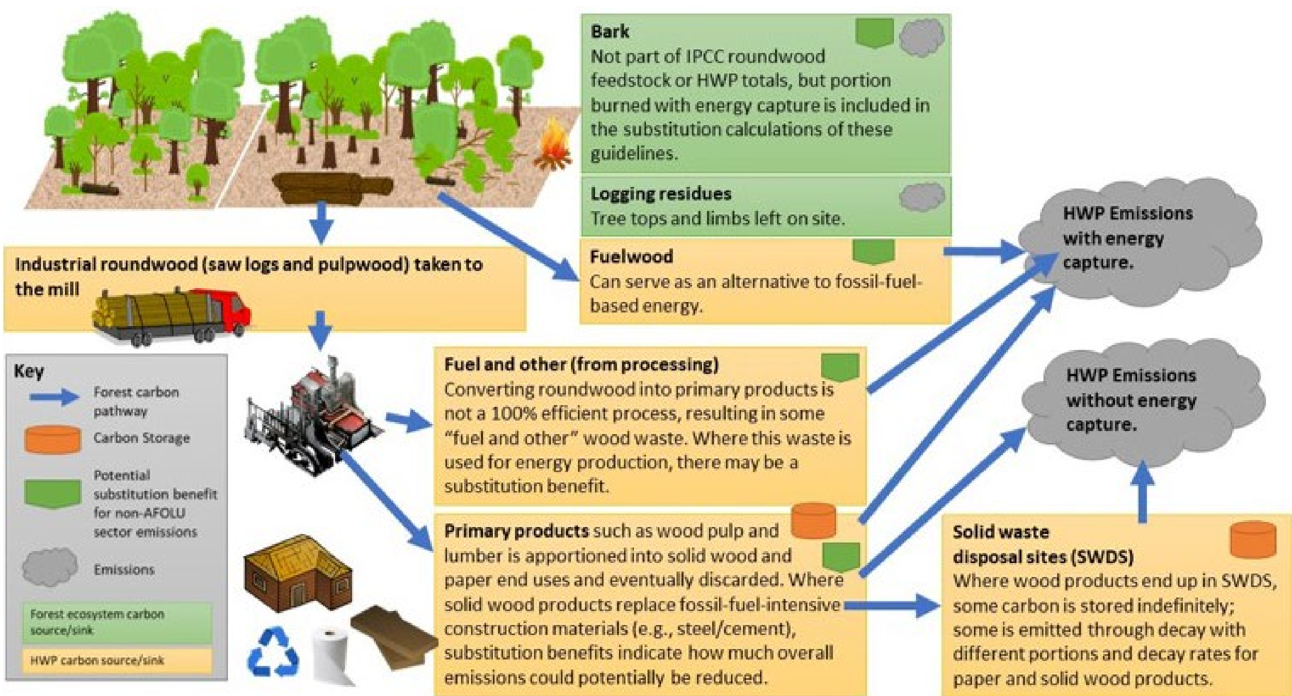
Table 5-3. Pools and Gases Relevant in Quantifying GHG Flux for Forest Management

Pools and Gases	Considerations
Live trees	This is a major carbon pool and relevant to quantification.
Understory	It is best practice to include understory carbon for completeness, but it is rarely significant for reforestation activities. However, in terms of forest ecosystem dynamics, understory attributes can greatly affect tree regeneration and survival rates.
Standing dead	Depending on stand age and disturbance history, may be relevant to quantification. For completeness, it is best practice to include. It is expected that, if tree mortality starts to increase due to global change, this pool will become more important in determining flows of forest carbon.
DDW, also known as coarse woody debris	Depending on stand age and disturbance history, may be relevant to quantification. It is best practice to include DDW for completeness, but it is rarely significant for reforestation activities. In the case of wildland fire, deadwood and forest floor pools are the largest immediate sources of emissions.
Forest floor	For completeness, it is best practice to include. For reforestation activities, this carbon pool is rarely significant. In the case of wildland fire, deadwood and forest floor pools are the largest immediate sources of emissions.
Forest SOC	For most North American forest types, soil carbon accumulation may be omitted: it is likely to change at a slow rate and is an expensive pool to measure. Accruals within the first 25 years may not represent a significant proportion of carbon stocks, and therefore could be considered *de minimis* in many cases. Exceptional cases, such as wet high-carbon peatland forests, may need more consideration.
Products in use	If feasible, and if forest harvesting takes place, products in use are relevant to quantification. For completeness, it is best practice to include because a significant proportion of forest carbon stocks can be stored in HWPs.
HWPs in SWDS	If feasible, and if forest harvesting takes place, HWPs in SWDS are relevant to quantification. For completeness, it is best practice to include because a significant proportion of products in use are either temporarily or permanently stored in SWDS.
CO_2	This GHG is very relevant to quantification.
CH_4	Depending on the forest management activity, may be relevant to quantification. The land-use sector accounting does not typically include CH_4 emissions from reforestation, extended rotation, and avoided deforestation activities. However, they may be important for addressing impacts of wildfire or prescribed fire (covered in section 5.2.2).
N_2O	Depending on the forest management activity, may be relevant to quantification. GHG impacts from reforestation, extended rotation, and avoided deforestation activities within land-use sector accounting do not typically include N_2O emissions, especially if the site is not fertilized. However, N_2O emissions may be important to consider in addressing the impacts of wildfire or prescribed fire (covered in section 5.2.2).

5.1.4 Management Interactions

Forest management activities can cause carbon to move between different carbon pools in the forest ecosystem, into HWPs, and to/from the atmosphere. They may influence the amount of total carbon stored in a forest ecosystem, as well as the amount of carbon that is stored in HWPs or SWDS when transferred out of the forest ecosystem pools.

Some forest management activities will result in accelerated loss of forest carbon through soil disturbance (i.e., through accelerated oxidation of soil organic matter), or when prescribed burning releases CO_2 and other GHGs. Forest management may also require the use of equipment that is powered by fossil fuels. For example, when a site is cleared, carbon may move from the live trees into harvested wood, and some of the wood carbon may also be released into the atmosphere via decay or burning of the harvested wood (see figure 5-2). When a site is planted, growing trees' carbon increases as they remove CO_2 from the atmosphere and store it in their living biomass. In some cases, a forest management practice emits carbon but causes a long-term improvement to gross CO_2 removal via forest growth and resilience, resulting in more net carbon stored in the forest through time. Some fuel management activities, for instance, may lower carbon stocks by removing fuels (biomass) from the landscape over short periods but create a longer term carbon benefit by enhancing forest health and lowering emissions associated with avoiding potentially severe fire in the future. Accounting for the total net flux (both emissions and carbon removals) and the relative timing of these changes is an important part of ensuring completeness in quantification. The net carbon results of any activity will be the net sum of all the individual effects (i.e., emissions and carbon removals) across different carbon pools and time scales.



Emissions featured in this figure are GHGs and do not reflect other air pollutants. AFOLU = agriculture, forestry, and other land use; HWP = harvested wood product; IPCC: Intergovernmental Panel on Climate Change (United Nations); SWDS = solid waste disposal sites

Figure 5-2. Diagram of Carbon Flux: Pathways Forest Carbon Can Take to the Atmosphere

Natural disturbances such as drought, wind or flood events, wildfire, insects, and disease convert live vegetation to dead, altering carbon dynamics. They may reduce carbon captured by photosynthesis in the short run due to reduced vegetative cover and increase emissions from decomposition of dead vegetation.

In addition, there may be interactions between biological and physical processes that are affected by forest management treatments or natural disturbances—for example, changes in albedo (reflectivity) during forest regeneration after wildfires, as discussed in appendix 5-C. Applied research in this field is in the early stages, so this guidance does not discuss such interactions.

5.1.5 Accounting Boundaries

Clearly defining and delineating boundaries helps avoid double-counting, imbues transparency around what estimates do or do not include, and helps ensure efforts to measure and monitor emissions or carbon removals can be undertaken in a comparable way over time.

The following sections describe the types of boundaries to consider in forestry entity-scale reporting.

5.1.5.1 Spatial Boundaries

The spatial boundary is the geographic area in which project activities take place. For this chapter, this is defined as the extent of the landowner's property. However, these guidelines recognize the complexities within ownership arrangements across forested lands and may also be applicable to communal lands or other complex multi-landowner entities governed by a documentable, coordinated management regime. The key consideration is capturing all the interrelated land use decisions made by the managing entity to avoid missing GHG emissions/carbon removals from management activities in the accounting (to the extent possible). Such exclusions would give misleading estimates of the impact of an entity's decisions. Explicit guidance on delineating spatial boundaries is offered in sections 5.2.1, 5.2.2, 5.2.3, and 5.2.4 below.

The carbon pools that fall within the sector boundaries are described in table 5-3. Where harvesting occurs, some of the carbon pools that should be accounted for are located outside the landowner's property as HWPs are transported to the mill and become "products in use" or enter SWDS (see figure 5-2).

Stratification is an important concept in delineating land areas appropriately for the purpose of monitoring and assessment. Forests within an entity can be highly variable in composition and structure and subject to a range of management activities, which all may affect the amount of carbon stored and released over time. Delineating and grouping land into homogenous units—"strata"—can help reduce sampling effort, increase the accuracy and precision of accounting by reducing field data variability, and make it possible to apply different quantification approaches/assumptions based on management practices or biophysical conditions.

Land could be partitioned, for example, by forest type, productivity class, management intensity, and/or average tree age for even-aged stands. Forest strata will often, but not necessarily, be contiguous. The landowner can choose the stratification scheme to employ. A good stratification approach can increase the accuracy and precision of carbon estimates and potentially lower the extent of data collection needs and associated resources.

For instance, a reestablishment project may undertake two distinct interventions within the boundaries of the landholding, one for a commercial plantation and the other for natural regeneration. These areas would be stratified into two stands, as they have different carbon sequestration rates. If the project or property is to be a single forest cover, such as a natural regeneration forest or a plantation forest, the project site can be a single stratum, but other factors may be important, such as land slope or soil conditions, that may significantly impact the carbon outcomes for the same activity. Box 5-7 in section 5.2.1.1 provides resources on designing sample-based inventories and stratification.

Note that many mapped products or methodologies that are available at the regional and national scale can, using relatively simple GIS operations, predict carbon (or biomass) over a specified area, including at the individual entity level (Riley et al., 2021; Ohmann and Gregory, 2002). While these mapped products may be very useful for stratification or regional planning, their carbon predictions in small areas may be highly uncertain. They may not be appropriate sources of direct estimates of carbon, or carbon change, at the entity level.

5.1.5.2 System Boundaries

System boundaries reflect what activities will be accounted for, what the relevant GHGs are, and what carbon pools will be included. In other words, they pertain to defining the types of emissions considered and where they originate. The carbon pools and GHGs that fall within the sector boundaries are described in table 5-3.

Estimation methods presented in this section are for forest management activities. However, these activities may interact with animal agriculture or croplands and grazing lands. Users should refer to other chapters for relevant guidance on estimating GHGs from those sources to ensure complete accounting that avoids double-counting. In addition, any land-use transitions that occur within a property must be accounted for so that apparent changes in carbon stocks or fluxes are “real,” not the result of an unrecorded transfer from one sector to another.

5.1.5.3 Sector Boundaries

This guidance primarily is limited to GHG accounting within the agriculture, forestry, and other land use (AFOLU) sector, but forest management activities may induce GHG impacts across multiple sectors. (See chapter 2 for more details on sectors.) The majority of methods in this guidance do not represent life cycle assessment (LCA) approaches. The exception is the methods for HWPs: because HWPs play a significant role in the overall GHG impact of forest management activities, understanding the emissions impact of processing and transporting them can inform a more complete picture. Accordingly, section 5.2.1 does expand into an LCA approach for HWPs. LCAs are typically used to evaluate GHG emissions for a specific material or product. They tend to span sectoral boundaries; businesses use them to evaluate GHG emissions from raw material extraction, processing, manufacturing, and transportation through disposal of a product, material, or service.[2]

The machinery employed to harvest, transport, and process timber derives energy from the combustion of fossil fuels. Energy is a separate emissions sector, and therefore these guidelines do not address fossil fuel emissions from silvicultural practices, with a few exceptions:

- For a more holistic understanding of the GHG impact of forest management activities, estimates of potential emission reductions from wood product substitution are offered in the HWP methodologies described in section 5.2.1, which offers a means to quantify the fossil fuels emissions through a cradle-to-gate LCA (from where a tree was grown to leaving

[2] See https://epa.gov/sites/default/files/2016-03/documents/life-cycle-ghg-accounting-versus-ghg-emission-inventories10-28-10.pdf for more information on GHG emission inventories versus LCAs.

the forest boundary when harvested and transported off site). Where sectoral boundaries are breached to offer a more complete estimate of GHG fluxes from forest management activities, these estimates will be calculated and presented separately in the accompanying Excel workbook for "Level 1" estimates with ample justification and guidance on application.

- This chapter references i-Tree software tools for quantifying GHG impact estimation in the urban forest context. Some of these do offer means to quantify emissions from forest maintenance, focusing on fossil fuel use in machinery.

Fertilizers applied as part of forest management practices also need energy to produce and transport, but that energy may be offset by the additional growth in biomass they are designed to trigger (see box 5-3). As stated in chapter 2, this guidance limits GHG quantification methods to the AFOLU sector, with limited exceptions.

Box 5-3. Emissions from Fertilizer Application

Fertilizers influence net GHG flux in a holistic sense: their production requires energy; the use of nitrogen-based fertilizer release GHGs such as N_2O after application; and they may increase tree growth and sequestration rates. These interactions are complex and take place across multiple sectors. Research in western Canadian forests showed soil GHG fluxes were neutral following fertilization (Basiliko et al., 2009). In an analysis of fertilization of pine plantations in the southeastern United States, Albaugh et al. (2012) found carbon sequestration in forest growth far exceeded the emissions associated with fertilizer production, transport, and application (8.70 Tg/year CO_2 sequestration vs. 0.36 Tg/year emissions). Thus, forest fertilization when applied appropriately can dramatically increase carbon sequestration. Given these complexities, emissions from fertilizer application within forest management activities are not included in this chapter, with the exception of emission factors in the "Level 1: LCA Method for Quantifying HWP GHG Emissions" section (within section 5.2.2.1).

Products from forest management practices are also linked to other sectors of the economy; for example, forest managers' decisions can dramatically affect GHG emissions in energy production, construction, or agriculture. In the case of wood product substitution (covered in more detail in section 5.2.1), harvested wood can be used in construction or manufacturing to reduce the need for materials with a larger GHG footprint, like plastic, steel, and concrete.

Although these external impacts are often context-specific, require substantial assumptions, and are difficult to specifically quantify, it is important to note that these outside GHG impacts can at times be as large as or larger than the GHG changes within the entity boundaries. Similarly, new activities or economic shifts outside the forestry sector can have an influence inside the forestry sector. Even where these impacts cannot be quantified according to this guidance, they should be considered to the extent possible when evaluating the desirability of a management action for GHG mitigation to avoid misleading estimates of GHG performance and perverse impacts.

5.1.5.4 Temporal Boundaries

GHG accounting for forest management activities presents challenges related to time scales that may not occur in other sectors or agricultural activities. Agricultural products often mature in an annual cycle, but forestry operations occur over multiple years and decades. Furthermore, while annual estimation and reporting are sometimes required, annual measurements of forest carbon pools are not generally economically feasible, nor are changes in carbon stocks generally detectable within acceptable error levels on an annual basis. This necessitates the use of forward-looking models and projections to assess the GHG consequences of management practices and evaluate the possible benefits of a change in management practices over decadal time scales. These forward-looking projections should consider future management activities that can be reasonably foreseen due to management plans, landowner intent, or reasonably predictable consequences of management decisions.

GHG sequestration or emissions from forestry practices are also not necessarily consistent over time. For example, a newly established forest will take up carbon slowly at first, then pass into a period of relatively rapid carbon accumulation. The carbon uptake rate will then typically decline, sometimes leveling off as growth is balanced with mortality in many older forests. This is why carbon sequestration rates (i.e., carbon removal factors) for a single forest type are sometimes grouped into age classes to more accurately portray the rate at which they remove carbon from the atmosphere through time (see section 5-A.1.2 for a more complete description of "removal factors"). Because older forests tend to have lower rates of active carbon sequestration but higher overall carbon stocks, it may not be possible to maximize carbon stocks and sequestration simultaneously.

Furthermore, more resilient forests may have less carbon stored in them than overstocked or unhealthy forests. While standing live tree biomass may not increase substantially, carbon may continue to flow into other forest carbon pools until the forest is disturbed by harvests or natural means. This guidance does not attempt to determine the appropriate level of carbon for a project area or forest, but rather allow landowners to understand the GHG implications of their management activities.

Collectively, the diversity of forest ecosystems across the United States develops at varying rates, depending on a host of variables including species composition, ecological conditions and climate, management and disturbance history, and management practices. No set temporal scale for accounting is therefore offered in this chapter, though estimates for GHG emissions and removal produced by the simple Level 1 approach supported by the accompanying Excel workbook in this guidance apply a 50-year boundary for GHG emissions and carbon removals from silvicultural practices (on the forest ecosystem side) and a 100-year boundary for the carbon stored in HWPs (see section 5.1.6 for a summary of the selected methods and descriptions of "Levels"). Due to large uncertainties about long-term consequences of fire as well as future management activities and disturbances (e.g., future fire), the temporal boundaries used in the wildland fire emission estimates in this guidance are limited to immediate fire effects. It is acknowledged that postfire vegetation regrowth represents a future carbon sink, and the current omission of this component under the Level 1 approach renders an incomplete account of the impact of fire. Future versions of this guidance are expected to include postfire vegetation regrowth under the Level 1 approach.

The variability of forest GHG dynamics over time also depends on the characteristics of the forest ecosystem and the products produced from it. For example, a forest fuel reduction project may create GHG emissions by releasing stored carbon in the near term yet reduce the risk of future unplanned emissions for the entity or the larger landscape in which it is located in the medium to long term due to reductions in high-intensity wildfire or other disturbance. Materials created by the fuel reduction project may also continue to store portions of the forest carbon for years or decades as wood products and eventually in landfills (SWDS).[3]

[3] Though landfills may also be a significant source methane emissions, depending on design and management practices, offsetting any storage benefit.

Box 5-4. The Stochastic Nature of Unplanned Disturbances

Further complicating GHG accounting within the forestry context is the stochastic (random) nature of unplanned disturbance events over the lifetime of a management practice. For example, a forest stand with an approximately 50-year fire return interval may not experience any fire disturbance for 80 years, but then experience a second fire at only a 15-year interval. The net GHG implications over time of a management intervention that creates near-term emissions will depend heavily on this inherent variability. Therefore, it is very challenging to quantify the future unplanned emissions of a forest entity without either making largely unknowable assumptions about the future or using probability modeling such as Monte Carlo simulation approaches. This is further complicated by climatic changes, policy interventions, technological advances, and other factors that are continuously changing the probabilities and future risks of GHG emissions from these systems.

There are no "correct" answers to balancing such near-term vs. longer term fluxes, and judgments of the desirability of these management actions will depend heavily on assumptions about future disturbance/emission risks, entity values and preferences, and other emissions occurring outside the entity boundaries in other sectors.

5.1.6 Summary of Selected Methods

As shown in table 5-4, this chapter describes methods for estimating emissions or carbon removal from silvicultural practices and improved forest management, carbon storage and emissions and LCA-quantified substitution impacts from HWPs, emissions from wildfire and prescribed fire, and GHG flux from urban forest management. The specific method to choose depends in part on circumstances unique to each entity, but even more on the intended use of the estimate and the resources available to quantify and/or monitor emissions.

At the entity scale, repeated annual remeasurements are not practical in most cases, nor are the annual changes in carbon stocks significant enough to justify annual remeasurements. Instead, data from published studies or reputable sources or projection models (e.g., lookup tables) can be used to account for carbon stock losses or gains (Janowiak et al., 2017). Appendix 5-A.1 provides general background on activity data (including discussion of stock-change and gain–loss) and a summary of the type of estimates within these methods.

This chapter offers options, called "Levels," of approaches to generating estimates for each forest management activity. The methodologies and underlying data for each Level confer a particular level of accuracy and data accessibility, as well as cost. Generally, where higher accessibility is achieved, accuracy is sacrificed. Nevertheless, each approach offered is considered scientifically sound and grounded in fully credible data and methodologies. The Level 1 approaches offered in this chapter can be considered comparable to an IPCC Tier 2 approach, applying region-specific data and reflecting an intermediate level of methodological complexity. Levels 2 and 3 could be considered congruent with IPCC Tier 3. While not all of the forest management activities included in this chapter offer all three Levels, at least one Level 1 option is proposed for each activity. Users may use different Levels for the different forest carbon pools (e.g., Level 1 for DDW but Level 3 for standing live trees), but this variability does not exist in the accompanying Excel workbook. (See table 5-5 for more information on the Excel workbook.)

- **Level 1** approaches are most accessible and are envisioned to enable generalized estimates of GHG flux from a limited set of forest management activities requiring only basic user inputs. Applying the ''gain–loss" approach to GHG inventories (see appendix 5-A.1.2), users need minimal information to estimate current carbon stocks, associated GHG flux (i.e., combining area of intervention with relevant emission or removal factors), and potential impacts from selected forest management activities. For forest management activities included in the accompanying Excel workbook, users enter basic information such as the location and land area (acres) of the area in question; the tool will draw appropriate data from built-in data (i.e., "lookup tables") to produce estimates. This workbook is meant to facilitate the estimation of GHG flux for a broad range of users and is an initial demonstration of often complex calculations across system boundaries (ecosystem to HWP to decay/combustion). As described in chapter 2, users can either calculate a "basic projection" or estimate the impact of a management change. A basic projection offers a prediction of the carbon flux of a forest parcel that is maintained (similar to a baseline, status quo, or business as usual scenario). Estimated impacts from a management change require a comparison between the baseline as well as the management intervention scenarios. The difference between these scenarios represents the net impact of adopting the management practice.

- **Level 2** approaches generally apply the same methodologies as offered in Level 1, but require more proficiency in forest carbon accounting and data access/knowledge. Users can choose locally relevant emission factors or removal factors to apply rather than the regional defaults used in Level 1 estimates. For example, inventory data for Level 2 or Level 3 approaches might be obtained from extension foresters, or for Tribal lands from the Bureau of Indian Affairs' Continuous Forest Inventory (obtained through the Bureau's Branch of Forest Resources Planning).
- **Level 3** approaches involve direct measurements and/or more complex modeling approaches that represent a more advanced user's needs and capacities and a higher level of certainty in forest carbon accounting. For example, the FVS (Forest Vegetation Simulator) modeling software, used by the USDA Forest Service and others, models individual tree growth and requires users to apply a geographically explicit list of trees.

More specific information on the Levels and data needs for various activity estimations is included in the sections on specific activity estimations, as summarized in table 5-4. Reference table 5-5 for the structure of the accompanying Excel workbook. Below, the sections on individual methods describe the user input needed to use the Excel workbook.

Table 5-4. Overview of Managed Forest System Sections, Sources, and Methods

Section	Source/Forest Management Activity	Estimation Method
5.2.1	Silvicultural practices and improved forest management	Level 1: Applicable for basic projections of carbon flux reflecting broad forest maintenance practices or broad forest maintenance practices with a harvest, as well as scenario-based comparisons of reforestation, extended rotation, and avoided deforestation. The Excel workbook combines basic user-provided activity data with preprocessed lookup table values (carbon stocks and stock change specific to regions/forest type group/age classes/stand origin).
		Level 2: Applicable for basic projections, reforestation, extended rotation, and avoided deforestation. Level 1 quantification approach without the Excel workbook, using site-specific carbon stocks and carbon stock change data.
		Level 3: Applicable to a wide range of even-aged and uneven-aged silviculture and improved forest management practices. Inventory data combined with model simulations—e.g., FVS.

Section	Source/Forest Management Activity	Estimation Method
5.2.1	HWPs	Level 1: Excel workbook–facilitated computation to estimate the carbon stocks of products in use, products in SWDS, emissions from HWPs, and potential substitution benefits over a 100-year timeline. Results may or may not be combined with silviculture depending on user inputs (i.e., users may select the “Harvest” option which does not provide estimates of flux from tree growth).
		Levels 2 and 3: None offered.
5.2.3	Wildfire/ prescribed fire	Level 1: Excel workbook–facilitated computation. Applies preprocessed lookup table values offering estimated emissions according to three fire scenarios: severe, moderate, mild/prescribed burn. Estimates are grouped by forest type group and region. These results are generated independently from the silviculture calculations.
		Level 2: None offered.
		Level 3: Inventory data combined with model simulations—e.g., FVS with the Fire and Fuels Extension (FFE) or FOFEM (First Order Fire Effects Model).
5.2.4	Urban forest management	Levels 1, 2, 3: Selection of i-Tree tools based on the input data available and desired scope of emissions to account for.

Note that ongoing measurement and monitoring should take place after the forest management activity begins. This monitoring phase characterizes a project’s impacts better than projections can. Annual measurements are usually either logistically impossible or too time consuming and expensive; rather, measurements are recommended every 5 years after the initial measurement. It is best practice to create and follow a measurement and monitoring plan in keeping with the goals of the project, and to keep organized records of measurements. This chapter does not include details on methods for ongoing measurement, which can be sourced from published literature and guidance such as Pearson et al. (2007).

Table 5-5. Structure of Accompanying Excel Workbook

Excel Workbook Component	Tab Identifying Color	Excel Tab	Description
Guidance and context	Yellow	Instruction and Context	Provides an overview of the purpose of the workbook and user instructions.
		U.S. Regions	U.S. regional delineations as applied in the guidance.
		Acronyms, Tabs, Citations	Lists abbreviations used in the Excel workbook, tabs and their contents, and citations. Also contains text that offers possible explanations where calculator outputs render estimated emissions.
User data entry	Red	User Data Entry	Here, users choose the management activity to quantify GHG flux for, then enter data and/or select from dropdown menus to define the quantification scenario(s) (e.g., baseline or management).
			Immediate detailed results for some management activities are also dynamically shown: ▪ Changes in ecosystem carbon stocks from activities included in section 5.2.1. ▪ Estimated GHG emissions from fire.

Excel Workbook Component	Tab Identifying Color	Excel Tab	Description
Main results	Dark orange	Forest Management & HWP Results	For clarity, summarized results are presented as separate categories: ▪ "Ecosystem Carbon Impacts from Forest Growth": Change in living and dead carbon pools from the growth, mortality, and decay of forest biomass on site. "Ecosystem Carbon Impacts from Harvest": Proportion of total ecosystem carbon stocks transferred to HWPs or emitted as a result of harvest. ▪ "Postharvest Carbon Impacts": Harvested wood products in use, harvested wood products in SWDS, HWP emissions. This results in an estimate of additional carbon sequestered as a result of forest management activity. If the activity includes a harvest, the summary tables reflect the complete accounting approach, reflecting the magnitude of ecosystem carbon left on site, as well as in wood products and ultimately emitted or stored in products or SWDS.
			"Total AFOLU Biogenic Carbon Stock Change from Management Action": A final result is also shown, which reflects the estimated stock change (flux) in AFOLU sector carbon. Negative values confer sequestration; positive values reflect either emissions (emissions at harvest, HWP emissions from decay) or decreased stocks/stock change (storage in harvested sawlogs etc.).
			The "LCA Quantified Substitution Potential Associated with Harvest, Transport and Processing" area gives additional context, but is not presented as part of the total impact because some emissions fall outside the AFOLU sector.
		Fire Results	Estimates of emissions for three fire activity scenarios. See section 5.2.3 for details.
Detailed results for reference	Light orange	Harvest Carbon Calculator	Offers detailed annualized estimates of emissions and storage of HWPs under different decay functions across the full 100-year accounting timeline (see section 5.2.2 for details). Examples of calculations are given in appendix 5-B.2.2.
		Growing Stock Calculator	Offers detailed estimates of the harvest volumes by roundwood product types (see section 5.2.2 for details). Examples of calculations are given in appendix 5-B.2.2.
		Potential Substitution	Quantified potential substitution benefits occur outside the AFOLU sector and are intentionally presented separately and not combined with the AFOLU totals, in accordance with IPCC reporting.
		Various	Several other tabs with detailed outputs to calculations.
Lookup and reference values	Gray	Various	Back-end lookup tables are view-only. Additional gray-shaded tabs are included for transparency. Some include the values applied to calculations to render results.

5.2 Estimation Methods

5.2.1 Silvicultural Practices and Improved Forest Management

Method for Estimating Emissions or Carbon Removal from Silvicultural Practices and Improved Forest Management

- There are three Levels available for this sector, depending on data availability, user resources, and desired precision.
- For the Level 1 approach, the accompanying Excel workbook combines user inputs with relevant equations and regional lookup tables derived from the FIA Database (FIADB), and where appropriate, connects the silvicultural practices with the methods for quantifying harvest impacts, carbon stored in HWPs, and potential substitution.
- For a Level 2 approach, use the equations provided for the Level 1 approach accompanied with more site-specific removal or emission factors.
- The Level 3 approach requires users to combine inventory data with FVS modeling or a similar model to simulate management scenarios.

5.2.1.1 Description of Method

Forest management is commonly characterized in terms of silvicultural practices. These are practices that favor structural and compositional conditions that meet one or more landowner objectives. Traditionally, they have aimed to control the growth, composition, health, and quality of forests to meet objectives associated with commodity (e.g., timber) production with an eye to long-term sustainability. However, silvicultural practices are increasingly being used for other purposes such as to restore and enhance biodiversity; increase resilience against stressors such as insects, drought, or fire; and/or increase carbon accumulation and associated stocks.

Regardless of the management objective, silvicultural practices affect carbon dynamics, whether by increasing forest growth and changes in litter and detrital carbon stocks; altering the size distribution or composition of species or density of trees; or triggering a transfer of carbon from one pool to another.

If harvesting, some harvested carbon may ultimately be stored for years or centuries as a wood product, while some is left to decay and be released as emissions over shorter time scales. As such, the impact of silvicultural practices on carbon flux can manifest in a variety of ways such as a release of carbon to the atmosphere (i.e., emissions), storage of additional carbon in forests or resulting forest products, and/or additional climate benefits through substitution for more emissions-intensive materials (e.g., using wood as a building material instead of concrete).

When considering the appropriate Level for estimation approach, consider the availability of data and resources to perform sampling and modeling as well as the precision needed (e.g., a generalized estimate for basic understanding, a more precise one for reporting purposes). As shown in figure 5-3, the Level 1, Level 2, and Level 3 approaches in this section—and in the following sections—have different levels of accuracy and accessibility. See appendix 5-B.1 for a rationale of the method chosen to represent Level 1 in this section, including background on the lookup tables and underlying data sources. Appendix 5-C provides a list of some of the data gaps and future improvements.

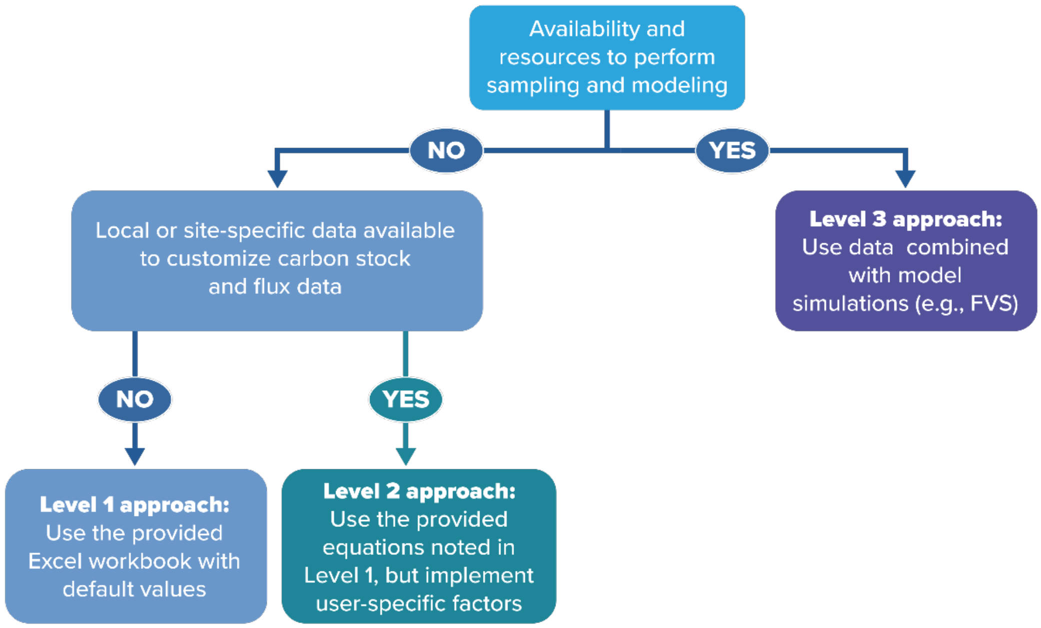


Figure 5-3. Decision Tree for Silviculture Practices and Improved Forest Management Levels

Level 1 Approach

The Level 1 approach is for entities with limited local data or knowledge of carbon quantification methods, or for entities seeking to produce a quick estimate of potential impacts from simple forest maintenance, reforestation, extending rotation, or avoiding deforestation. It relies on the accompanying Excel workbook, which has embedded lookup tables that offer regional default values for carbon stocks and stock change (i.e., "carbon removal factors" in this chapter). For some activities, the impact of harvest and the storage and substitution potential of HWPs can be quantified.

The lookup tables were constructed using data from the USDA Forest Service's FIA program (Burrill et al., 2021). They offer average forest ecosystem carbon stocks and stock change values, organized by region, forest type group, stand origin, and stand age (see appendix 5-B.1 for methods). The carbon stocks and removal factors include all carbon pools except SOC and standing dead tree carbon for carbon removal factors. In the case of SOC, changes in soil carbon stocks are assumed to be *de minimis* over the timelines/temporal scales in question, and there is a lack of available data on the impact specific forest management practices have on SOC at the entity scale. In the case of standing dead tree carbon, FIA measures standing dead trees but does not track individuals after their transition to fallen dead wood; therefore, closed system accounting for change methods for that pool requires further research.

As stated in section 5.1.6, Level 1 offers users the ability to generate two types of estimates: basic projection and estimated impact of a management change. Table 5-6 describes data inputs to apply the Level 1 approach, as well as some caveats.

The basic projection estimation type offers a generalized projection of carbon stocks and stock change for the user-selected combination of region, forest type, age class, and stand origin. It is offered for forest maintenance with or without harvest. The section providing the estimated impact of a management change is applicable for a limited set of initial, generalized categories of silvicultural practices—extended rotation, reforestation, and avoided deforestation management options—and offers scenario-based comparisons (details on these practices are included in the section below and in appendix 5-B.2).

Given the granularity of the Level 1 approach, more sophisticated forest management interventions such as advanced silviculture or fertilizer applications are not included, but advanced users may be able to incorporate such operations in Level 3 approaches. Operations such as fertilizer applications can have gross GHG emissions associated with their production/application, as well as potentially a net reduction in GHG when considering resulting increases in forest growth/regrowth (as discussed in box 5-3). See appendixes 5-A.2 and 5-B.1 for more background information on these practices.

The more closely a user's selection of region, forest type group, age class, and stand origin align with the status of the current or proposed stand, the more likely results will be realistic. See the stratification discussion in section 5.1.5.1 for more on dividing management areas up into meaningful, internally homogeneous units (strata).

Where the specific forest type group, stand origin, or stand age class are not known, use the "unknown" option when entering parameters for the estimation of carbon stocks and flux in the Excel workbook. This option uses the area-weighted average value associated with the stand characteristic (or combination of characteristics, if multiple are unknown) within the selected region from the lookup table.

Box 5-5. Increasing the Transparency and Repeatability of Carbon Monitoring/Accounting Approaches through Open-Source Code

To increase the trust and accountability associated with carbon quantification tools, the data and associated computation processes used to develop emission/removal factors in this document is provided as an accompanying resource for these guidelines. Advanced users interested in evaluating how the lookup table values were derived and/or replicating or modifying the Structured Query Language (SQL) query approach used to construct the lookup tables can view the provided SQL code.

Table 5-6. Required Silviculture and Improved Forest Management User Data for the Accompanying Excel Workbook

Data Input	Description/How Data Are Sourced/Relevance
Area of intervention/ area of stratum	The area in which the entity anticipates undertaking the silvicultural activity. The Excel workbook assumes that entries are associated with a single stratum (such as a stand or group of stands). To generate results for multiple strata (such as forest stands with different stand origins), aggregate results from various strata with multiple runs of the tool. The workbook allows users to choose the units—acres or hectares. See section 5.2.1.2 for more information on how these area data values can be determined.
Region	The broad geographic region in which the silvicultural activity will take place. See figure 5-4 for a map of how the geographic regions are delineated.
Forest type group[a]	The forest type group that best matches the forest stand that will be subject to the forest management activity. See Burrill et al. (2021), appendix D, for detailed descriptions of the species composition of the forest types that constitute forest type groups. Choose "unknown" if the forest type group is not known.

Data Input	Description/How Data Are Sourced/Relevance
Stand origin	Whether the stand was planted or grew naturally. Choose "unknown" if the stand origin is not known.
Stand age class	The age range of the forest stand. Forests accumulate carbon at different rates, so knowing stand age class renders a more accurate estimate of annual and total carbon accrual from the anticipated activity. Choose "unknown" if the stand age class is not known. For planned reforestation activities, entries for this component are not considered.
Type of management treatment	The "User Data Entry" and "Forest Management & HWP Results" tabs display different options depending on the selection. ▪ **"Basic projection under forest maintenance (fm)."** Assumes no harvest**.** The results show the total amount of carbon sequestered up to 50 years from the present time (time 0). ▪ **"Basic projection under fm, with harvest."** The results show the total amount of carbon sequestered between time 0 and the specified planned harvest time. Outputs are combined with the harvest carbon calculator outputs, including estimates of carbon flux in HWPs. ▪ **"Extended rotation."** The results show the carbon benefit from deferring harvest in even-aged[b] stands. The results reflect the difference between projected carbon stocks under the "baseline" planned harvest date and the extended rotation harvest date. Outputs are combined with the harvest carbon calculator outputs, including estimates of carbon flux in HWPs for both the baseline and extended rotation scenarios. ▪ **"Avoided deforestation."** The results show the carbon that remains stored as a result of avoiding deforestation that would have occurred at time 0 under the baseline scenario, including the estimated carbon sequestration over 50 years (i.e., includes the benefit of sequestration that would have been foregone if the deforestation event happened). ▪ **"Reforestation (natural)"** or **"Reforestation (planted)."** The results show the projected total amount of carbon sequestered over 50 years. The baseline scenario is assumed to be no carbon accrual. ▪ **"Harvest."** This option does not compare silvicultural treatments and just quantifies GHG flux from harvest at time 0**.**
Length of rotation/harvest	If "Basic projection under fm, with harvest" or "Extended rotation" options are selected, users must enter the rotation date (5-year increments). For extended rotation, 2 rotation years are needed: (1) harvest under the baseline scenario and (2) harvest under the extended rotation scenario.

[a] The forest types in this chapter correspond to the "forest type groups" described in the FIADB phase 2 user guide (Burrill et al., 2021, appendix D). These forest types are also listed explicitly in table 5B-11.

[b] Even-aged forests typically consist of trees that are in a limited number of age classes (one or two, e.g., 0 to 20 and 21 to 40 years old).

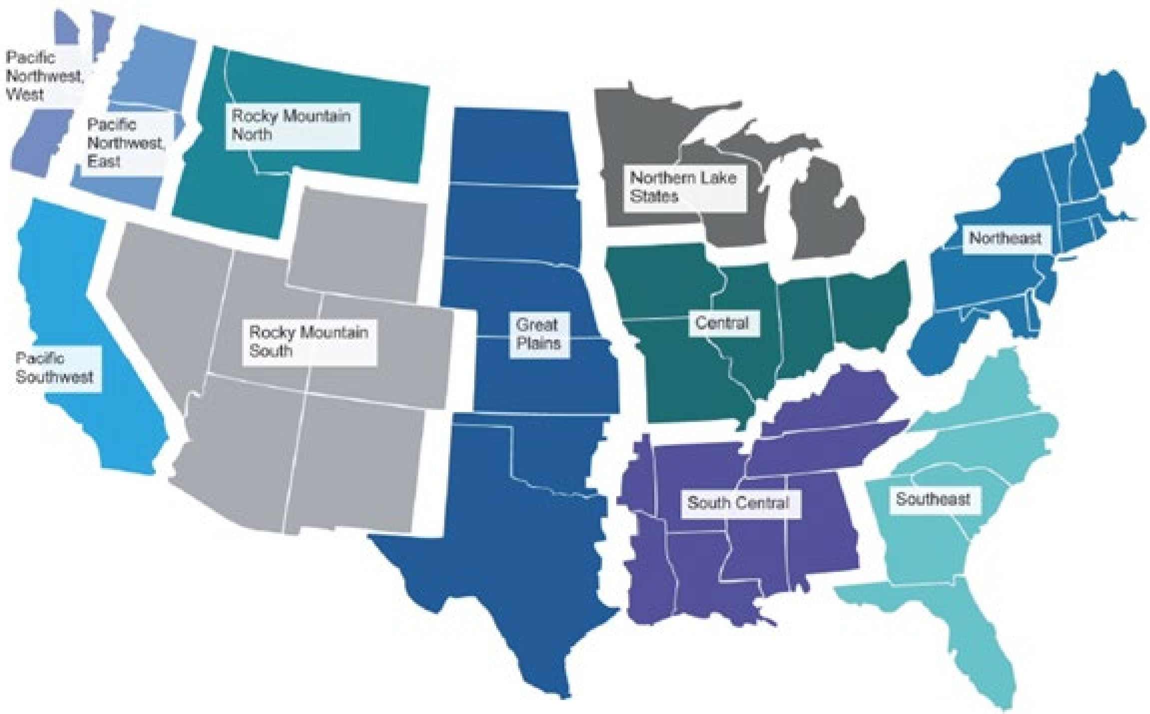


Figure 5-4. Forest Regions Applied to Organize Lookup Table Values for the Silviculture, Fire, and HWP Components of This Chapter

The methods and equations for combining lookup table values with activity data are described below. For some scenarios a user might create, seemingly illogical values (such as net emissions from a forest stand rather than growth) can occur if the lookup table data are generated from sparse forest inventory data. While these values could be valid—for example, in areas where fire, insects, or disease are causing net emissions from forests—care must be taken when interpreting them. If a value deemed illogical is rendered, options include:

- Choose “unknown” for the age class or stand origin in the Excel workbook. This will increase the number of values used to produce the lookup table estimates and may yield more reliable results.
- Undertake a Level 2 approach, looking elsewhere for more site-specific average carbon stock or stock change estimates to integrate as variables into Level 1 formulae described below.

See appendix 5-A.2.6 for more background information on the lookup tables used for this approach.

Any attempt to project forest growth dynamics should consider results within the context of location-specific disturbance risks (e.g., fire, insect, disease, temperature extremes, flood, and drought) and planned management and oversight to maintain the forest stand and its carbon stocks. The default lookup table values for carbon stocks and carbon stock change (i.e., carbon removal factors) have been produced using FIA data, so they inherently reflect background rates of tree growth and mortality seen across current U.S. landscapes. Where higher mortality is expected or observed during measurement and monitoring phases, users may need to consider discounting projections of carbon accumulation or taking a Level 2 approach that applies more site-specific removal factors.

Although the Excel workbook offers projected carbon sequestration for included activities for up to 50 years into the future, the further into the future a projection is made, the greater the uncertainty. In the Excel workbook, cells for years 25–50 in the "Detailed Ecosystem Carbon Scenario Projection" part of the "User Data Entry" tab are shaded as a reminder to users to consider the high uncertainty associated with projections that far into the future.

Ecosystem Carbon Accounting with HWP Carbon Accounting Linkage

This chapter presents silvicultural practices and improved forest management (this section) and HWP (section 5.2.2) separately, though these activities are connected through harvesting. The "ecosystem" side of carbon accounting described in this chapter covers carbon accumulation in living and dead biomass, as well as living and dead biogenic carbon flux because of harvest, such as that occurring from decomposition of logging residues. The HWP section considers the harvested wood that reaches the mill and is converted to wood products and mill residues (products in use), some of which decompose or ultimately end up in SWDS.

This guidance and the accompanying Excel workbook, under a Level 1 approach, connect the ecosystem accounting with HWPs by presenting HWP results in the context of FIA-based estimates of total ecosystem carbon stocks and management scenario impacts prior to harvest (equation 5-1 and equation 5-2) and estimates of logging residues calculated using regional factors derived from the literature (i.e., Smith et al., 2006; Johnson, 2001).

When the user selects activities that result in a harvest (i.e., "Basic projection under fm, with harvest," or "Harvest,"), the Excel workbook offers two options, advanced and default, based on user-supplied yes/no answers to the question "Do you know what your harvest volume is?" For extended rotation scenarios, only the default data option is available.

- **Advanced option:** Enter harvest data such as known harvest volumes or weights from logging/mill receipts or consultant reports, wood types (hardwood, softwood, unknown) and product types (sawlogs, pulpwood, fuelwood, unknown) as totals or per-acre values, as well as percentage of total growing stock harvested.
- **Default data option:** Uses default FIA data on regional growing stock volumes (cubic foot net volume per acre based on user-selected parameters around region/forest type group/stand age class/stand origin) for medium- and large-diameter stands to estimate harvest amounts. These growing stock volume default values delineate what part of the total live tree biomass carbon pool could be targeted for harvest. However, these estimates do not definitively reflect the total volume of wood potentially removed at harvest, given that nonmerchantable trees (not part of growing stock volume estimates) are often cut and taken to the mill to produce pulpwood or used for fuelwood. Therefore, these values are used as a starting point to quantify the wood taken to the mill but adjusted using published ratios from Johnson et al. (2001) to incorporate region-specific estimates of fuelwood or pulpwood biomass that the cubic foot net volume estimates do not capture. For the basic projection and "Harvest" options, the growing stock volumes can be discounted by the entered harvest area percentage. For the "Extended rotation" management option, 100 percent of the area is assumed to be harvested as extended rotation forest management is assumed to be an even-aged forest management practice.

With these data, estimates of the carbon flux associated with HWPs and the GHG flux from potential substitution can be calculated (see section 5.2.2 for more on the HWP components of the Excel workbook).

The Excel workbook presents the results in two ways, depending on the management scenario selected:

- Net carbon impacts of the planned management activity
- Carbon stock changes from time 0 to the time of harvest or year 50

The following sections describe the calculations for the various management scenarios.

Basic Projections

To project the carbon impact of maintaining a forest stand as forest cover, the Excel workbook runs equation 5-1 for 5-year intervals between time 0 and year 50 or the date of harvest, then uses equation 5-2 to calculate the total amount of carbon sequestered over the scenario time period (see box 5-6 for a definition caveat). If a harvest is planned, the projection ends at the harvest year entered by the user.

Box 5-6. "Removals"

In this chapter, "removals" is used interchangeably with "sequestration" and thus refers to a removal of carbon from the atmosphere in keeping with carbon accounting terminology precedence.

In the FIADB (Burrill et al. 2021), and in the context of forest management operations, "removal" is used to describe harvest operations when trees are removed from a site.

Equation 5-1: Five-Year-Interval Gross Carbon Removals

$$Five\ Year\ Interval\ Carbon\ Removals_{rtpai} = A \times F_A \times RF_{rtpai} \times F_m \times CO_2MW \times 5i$$

Where:

Five Year Interval Carbon Removals$_{rtpai}$	=	5-year time step CO_2 removals due to forest growth in region *r,* forest type group *t,* with stand origin *p*, age class *a,* and 5-year interval *i* (metric tons CO_2)
A	=	area of stratum (ha or ac)
F_A	=	area unit conversion factor; 2.407 if hectares are entered, 1 otherwise
RF_{rtpai}	=	removal factor (i.e., carbon stock change) for region *r*, forest type group *t*, stand origin *p*, and age class *a*, with *a* adjusted for time interval *i* (U.S. tons C/acre/year); time interval adjustment occurs because the age class of a stand changes through time, so different removal factors must be used as time progresses (see equation 5-B-2)
F_m	=	U.S. to metric ton conversion factor (0.907 metric tons/U.S. ton)
CO_2MW	=	ratio of molecular weight of CO_2 to carbon = 44/12

In the Excel workbook lookup tables, if a given combination of the classification variables chosen by the user does not exist, the removal factor data are aggregated hierarchically, starting with stand origin, then stand age, then forest type group, until a valid combination is found.

Equation 5-2: Total Gross Carbon Removals

$$Total\ Carbon\ Removals_{rtpah} = \sum_{i}^{h} Five\ Year\ Interval\ Carbon\ Removals_{rtpai}$$

Where:

Total Carbon Removals$_{rtpah}$	=	the sum of *Five Year Interval Carbon Removals*$_{rtpai}$ (metric tons CO_2) for the combination of the above-defined stand characteristics *r*, *t*, *p,* and *a* at scenario time *h*
i	=	5-year increment
h	=	the final cumulative increment endpoint (e.g., the end of the last period of carbon accumulation)

In the case of basic projection over 50 years, h =10 (because increments are in 5 years, 5h = 50 years). In the case of basic projection with harvest, i = 5 and h = the year the user chose as the harvest year divided by 5 (because increments are accounted for in 5-year intervals)

For the "Basic projection under fm, with harvest," "Extended rotation," and "Harvest" scenarios, the Excel workbook uses equation 5-3 to estimate carbon in logging residues, which reflects the CO_2 emissions associated with the decomposition of biomass left on site (i.e., stumps, branches, leaves) conservatively assuming release of these emissions immediately after harvest. The logging residue fractions used in equation 5-3 are generated from a lookup table derived from Johnson's (2001) tables[4] and are selected based on the chosen region and wood type. If wood type is unknown, harvested growing stock volume is distributed across wood and/or product types as described in section 5.2.2. Residue fractions of harvest are calculated as logging residues from all sources divided by the total harvest from all sources (growing stock and nongrowing stock). For example, for the North Central region and softwood trees harvested, the logging residue fraction is calculated as 97,775 ÷ 381,515, or 0.26 (i.e., 26 percent of the overall harvest was left behind as residues).

Equation 5-3: Logging Residue Emissions at Harvest

$$EH = RW_M \times F_{LRrw}$$

Where:

EH	=	logging residue emissions at harvest (metric tons CO_2)
RW_M	=	roundwood at mill after growing stock calculator adjustments and unit conversions to metric tons CO_2, as described in section 5.2.2
F_{LRrw}	=	logging residue factor associated with region *r* and wood type *w*, calculated from Johnson (2001) tables, as described above

Estimated Impact from Management Change: Extended Rotation

For extended rotation scenarios, the Excel workbook runs equation 5-1 and equation 5-2 for both the baseline and intervention scenarios. In the case of extended rotation, the variable h is set to h_b for the year of the baseline harvest and h_e for the year of the extended rotation harvest. In the Excel

[4] Specifically, the values are derived from regional tables—table 2.9 (Northeast), table 3.9 (North Central), table 4.9 (Southern), table 5.9 (Rocky Mountain), and table 6.9 (Pacific Coast)—within Johnson (2001).

workbook, the growth of the forest stand under the two scenarios (baseline and extended rotation) is shown in 5-year increments, both as the stocks and as flux (5-year change), in the "User Data Entry" tab in the "Detailed Ecosystem Carbon Scenario Projection" part of the display. Extended rotation activities are assumed to be undertaken in even-aged stands, and therefore 100 percent of the stratum/project area is assumed to be subject to harvest. Background on extended rotation is available in appendix 5-A.2.2.

To ensure accounting conservatively captures postharvest regrowth under the baseline scenario, after the baseline harvest date, the age class (a) for the baseline case is reset to the 0–20 age class, and the appropriate removal factors from the FIA lookup table for the 0–20 age class, combined with the same region/forest type group/stand origin selections, are used in equation 5-1 and equation 5-2 to grow the harvested stand until the date at which the user chose to harvest under extended rotation, at which point overall impacts of extending harvest can be calculated using equation 5-4, which describes the net impact of extending the rotation length (i.e., carbon removals from the atmosphere).

The results from equation 5-2 under the baseline and extended rotation scenarios are then brought over to the "Forest Mgmt & HWP Results" tab in the Excel workbook to complete the scenario projection inclusive of the postharvest ecosystem carbon impacts and HWP and LCA analyses[5] (section 5.2.2). The ultimate benefit is the difference between the final estimates—"TOTAL AFOLU (Forest) Biogenic Carbon Stock Change (Flux) from Management Action and Harvest"—for the two scenarios, which embodies the total impact of extending the rotation length in terms of both ecosystem impacts and postharvest carbon storage and emissions.

Equation 5-4: Net Impacts

$$\begin{aligned} Net\ Impacts\ &= Total\ Carbon\ Removals_{management\ intervention\ scenario} \\ &\quad - Total\ Carbon\ Removals_{baseline\ scenario} \end{aligned}$$

Where:

Net Impacts	=	estimated impact change (metric tons CO_2)
Total Carbon Removals	=	total carbon removals (metric tons CO_2)

Estimated Impact from Management Change: Reforestation

For reforestation activities, the Excel workbook runs equation 5-1 and equation 5-2 for the intervention scenario to reflect carbon sequestration of either a planted or a natural stand of a given forest type and the appropriate age class, based on the years of growth since time 0. Under the baseline scenario, it is assumed no significant accrual of carbon stocks would happen in the absence of natural or reforested stands. In other words, the stand is assumed to start with the user-selected parameters for region, forest type group, and stand origin, and begin growing with the 0–20-year age class; as time passes, the age class transitions to the next higher one, as described above, so updated removal factors are used through time.

The Excel workbook runs equation 5-4 (using zero for $Total\ Carbon\ Removals_{baseline\ scenario}$) to calculate the net impact of the activity. This is because the Level 1 approach assumes the baseline scenario has zero net carbon flux (i.e., without the reforestation effort, the area would have zero

[5] This is the only full side-by-side analysis of harvest scenarios enabled by the accompanying Excel workbook because "Extended rotation" is the only available scenario comparison (i.e., estimated impact from change in forest management activity) that involves harvest in both scenarios.

change in carbon stocks). Where baseline carbon stocks are expected to accrue (i.e., trees would likely grow and accumulate more than a *de minimis* amount of carbon in the absence of a reforestation activity), it may be more appropriate to use a Level 2 approach that models baseline carbon accumulation and compares it to the reforestation scenario using equation 5-4. Background on reforestation is available in appendix 5-A.2.3 and 5-B.1.2.

Estimated Impact from Management Change: Avoided Deforestation

For avoided deforestation activities, the Excel workbook runs equation 5-1 and equation 5-2, as with the "Basic projection under forest maintenance" (no harvest) scenario. However, it also presents results from equation 5-5, and equation 5-6, allowing the user to add the standing stocks at year 0 (the assumed date of deforestation under the baseline scenario) of the forest to the calculations of annual removals. Under the baseline scenario, the forest is cleared immediately following time 0 and future carbon the forest could have sequestered is foregone. In the avoided deforestation scenario, the immediate loss of biomass carbon stocks is prevented, and carbon may be allowed to continue to accumulate over time in the vegetation. Background on avoided deforestation is available in appendix 5-A.2.4.

The calculation steps are:

1. Calculate forest carbon accumulation as described above using equation 5-1 and equation 5-2; results are associated with the avoided deforestation treatment. For the baseline scenario, deforestation is assumed to occur immediately after the starting point (year 0); the foregone sequestration takes place over subsequent years up to year 50. Therefore, *h* in
2. Equation 5-2 should be 10 (because increments are in 5 years, 5h = 50).
3. Calculate total standing stocks (equation 5-5).
4. Calculate benefits by adding total standing stocks to total carbon removals (equation 5-6).

In other words, apply equation 5-5 and equation 5-6 for total standing stocks and total carbon removals; for the baseline scenario apply only equation 5-5 for time 0, as harvest is assumed immediately following time 0.

Equation 5-5: Total Standing Stocks

$$Total\ Stock_{rtpa} = A \times F_A \times CS_{rtpa} \times F_m \times CO_2MW$$

Where:

$Total\ Stock_{rtpa}$ = total stocks of CO_2 for region r, forest type group t, with stand origin p, at age class a (metric tons CO_2)

A = area of stratum (ha or acre)

F_A = area unit conversion factor; 2.407 if hectares are entered, 1 otherwise

CS_{rtpa} = carbon stocks (U.S. tons/acre) for region r, forest type group t, with stand origin p, at age class a (U.S. tons C/acre); these values are from estimates found in FIA-derived lookup tables and include aboveground and belowground live and dead carbon, SOC, DDW carbon, and litter carbon (see equation 5B-1)

F_m = U.S. to metric ton conversion factor (0.907 metric tons/U.S. ton)

CO_2MW = ratio of molecular weight of CO_2 to C = 44/12

Equation 5-6: GHG Impacts from Avoided Deforestation

$$AvoidedDef_{rtpa} = Total\ Stock_{rtpa} + Total\ Carbon\ Removals_{rtpa}$$

Where:

$AvoidedDef_{rtpa}$	=	benefits from avoided deforestation activities (metric tons CO_2)
$Total\ Stock_{rtpa}$	=	total stocks of CO_2 in region *r,* forest type group *t,* with stand origin *p,* at age class *a* (metric tons); see equation 5-5
$Total\ Carbon\ Removals_{rtpa}$	=	total carbon removals (metric tons CO_2); see equation 5-2 (this is part of the equation because most U.S. forest stands are accumulating carbon; total carbon removals might be small or nonexistent for old growth forests)

The maximum value of 10*h* used under the Level 1 approach is 50 years, but projections this far into the future should be considered in the context of management plans and capacity (e.g., efforts to maximize survival and growth) as well as the potential for natural disturbances.

Level 2 Approach

The Level 2 approach is identical to the Level 1 approach except that rather than using Level 1's default data it uses locally representative data to create site-specific emission factors. Choose this approach where:

- Locally representative data are available from an existing forest inventory.
- Assumptions or context applied in the development of the default data do not fit the silvicultural activity of interest (i.e., do not reflect the unique attributes and delineation of forest stands within an entity). In this case, use alternative sources of carbon data to develop emission or removal factors, such as those from published literature, or USDA Forest Service FIA estimates such as found in the EVALIDator[6] or DATIM tool. Several potential sources of data and other tools for carbon estimation are presented in appendix 5-A.6. The updated *Estimates of Forest Ecosystem Carbon for Common Reforestation Scenarios in the United States* (Hoover et al., 2023) may be of particular use as an alternate dataset: It offers FVS-generated forest ecosystem carbon yield tables for a set of common reforestation scenarios, representing stand-level total volume and carbon stocks as a function of stand age, for 13 forest types within the United States.

When using a Level 2 approach, refer to the Level 1 approach and replace lookup table variables (removal factors and standing stocks) with alternate available data.

Level 3 Approach

Level 3 requires more resources and time, as well as the ability to conduct detailed and statistically appropriate forest carbon inventories coupled with appropriate biometric models (e.g., live tree allometry) and projection systems (e.g., FVS).

[6] EVALIDator draws from FIA data to produce estimates and sampling errors for selected forest attributes for an area of interest. It allows users to designate their own polygons. See https://www.fs.usda.gov/ccrc/tool/forest-inventory-data-online-fido-and-evalidator for more information.

Establishing Forest Carbon Inventories

Forest carbon inventories are composed of observations and measurements from a series of plots in the forest, describing the trees in each plot—species, diameter, height, etc. From these measurements, stand-level estimates of tree density (trees per unit area), basal area (cross-sectional bole area at 1.4 meters [4.5 feet] above the ground), species composition, and tree volume and biomass can be computed.

The description below is a very general discussion of some principles of forest carbon inventory establishment. It is not comprehensive guidance, as inventory methods for estimating the carbon among forest ecosystem carbon pools are well developed and fairly standard. Methods for measuring forest ecosystem carbon stocks are described in a variety of publications, including the IPCC *Good Practice Guidance for Land Use, Land Use Change, and Forestry* (IPCC, 2003), Pearson et al. (2007), and Hoover (2008), among others. As the FIA program is the federal program tasked with providing national-scale estimates of the U.S. forest carbon stocks/flux, documented inventory procedures from this program (USDA Forest Service, 2010a, 2010b) are also available and can serve as a basis for many facets of entity-level carbon reporting.

Detailed methods for forest carbon inventory are well described and available from a variety of sources, such as those listed in box 5-7.

Box 5-7. Resources for Establishing Forest Inventories for Carbon Estimation

- *Measurement Guidelines for the Sequestration of Forest Carbon* (Pearson et al., 2007): https://www.nrs.fs.usda.gov/pubs/gtr/gtr_nrs18.pdf
- *Standard Operating Procedures for Terrestrial Carbon Measurement* (Walker et al., 2018): https://winrock.org/document/standard-operating-procedures-for-terrestrial-carbon-measurement-manual/
- *Sourcebook for Land Use, Land-Use Change and Forestry Projects* (Pearson et al., 2005): https://openknowledge.worldbank.org/bitstream/handle/10986/16491/795480WP0Sourc0CF0Projects00PUBLIC0.pdf
- Winrock's sample plot calculator spreadsheet tool (Walker et al., 2014): https://winrock.org/document/winrock-sample-plot-calculator-spreadsheet-tool/
- *Allometric Equation Evaluation Guidance Document* (Walker et al., 2016): https://winrock.org/wp-content/uploads/2018/08/Winrock-AllometricEquationGuidance-2016.pdf
- *Quantifying Greenhouse Gas Fluxes in Agriculture and Forestry: Methods for Entity-Scale Inventory* (Hoover et al., 2014). https://www.usda.gov/sites/default/files/documents/USDATB1939_07072014.pdf
- *Module C-CS: Calculations for Estimating Carbon Stocks* (Goslee et al., 2016). https://winrock.org/wp-content/uploads/2018/08/Winrock-Guidance-on-calculating-carbon-stocks.pdf

For small entities such as farm woodlots or tree and forest stands, a complete inventory of carbon across relevant pools, strata, and project land may be feasible. For large areas, such an inventory is likely both infeasible (in terms of time and resources) and unnecessary, as a well-designed sampling strategy can render results with low uncertainty. Sampling involves installing sample plots in the project area using a sample design, which could include stratification into subregions (see section 5.1.5.1 for more information on stratification). Forest inventories commonly use a number of plot designs; a full discussion is beyond the scope of this document. The number of plots used affects the reliability of resulting estimates; using more plots generally leads to more trustworthy results. To improve results and lower costs, stratifying the area into homogeneous subregions is often a good practice. Certified professional forestry consultants can also provide support in forest inventory.

For carbon accounting, the most important data collected on inventory plots are related to the tree's geometry, such as its dbh and height. To translate these measurements into carbon estimates, allometric equations—which describe the relationship between these measurements and a tree's volume or biomass—are used. These equations are either species-specific or refer to a group of species with similar geometric and wood properties. Several comprehensive, nationally consistent, and widely cited sets of allometric equations for all tree species in the continental United States are available (e.g., Westfall et al., 2023; Jenkins et al., 2003; Chojnacky et al., 2014; Woodall et al., 2011): these may be a good place to start for entities wishing to produce carbon estimates based on their own forest inventory data. The Forest Service FIA program released updated national scale volume and biomass (NSVB) estimators (Westfall et al., 2023) which are based on whole stem volume equations that are additive across the components: stump, merchantable bole, and nonmerchantable top. This more accurately reflects regional and species-specific patterns of biomass distribution and growth.[7]

To arrive at sample-based estimates, tree-level biomass or carbon estimates are aggregated to the plot level, and these plot values are expanded to population-level estimates of total carbon stock, average carbon stock, and carbon flux using standard statistical estimators (Smith et al., 2003). There exist various generic values for stocks and carbon densities in the literature (e.g., U.S. DOE, 1992; Smith et al., 2006; IPCC, 2003, 2006), and more site-specific, detailed values can be derived using FIA's reporting tools such as the FIADB or by undertaking a carbon inventory (described in section 5.2.1 under the Level 3 approach). As this is an emerging field of research and data compilation (see Martin et al., 2018), site-specific values should be considered superior to generic values, especially for the more complex dead wood components (Harmon et al., 2013) that should incorporate decay reduction factors (Domke et al., 2011).

Using FVS for Carbon Modeling

The USDA Forest Service's FVS software (USDA Forest Service, 2022c) is an individual tree-level model that can simulate a variety of forest management practices. It enables forest growth simulation, quantifying vegetation change in response to natural succession, disturbances, and management. It applies inventory data to model forest growth and yield, estimating carbon as a function of those estimates. As such, it needs data such as slope, elevation, site productivity (i.e., site index), inventory design specifications, species, tree diameters, etc. Default values are available for some variables, but model outputs rely heavily on the assumption that standard forest inventory data are used. Those employing FVS to model stand carbon dynamics into the future should be aware that the model does not account for projected climate impacts on growth (if one does not request the FVS climate extensions) and that future carbon estimates (i.e., 20+ years out) have high uncertainty. Note that FVS was developed as a tool for foresters, and therefore may be difficult for untrained users. FVS training is available from USDA (https://www.fs.usda.gov/fvs/training/index.shtml).

[7] For more information, visit: https://www.fs.usda.gov/research/programs/fia/nsvb

See Hoover and Rebain (2011) for more information on employing FVS for carbon estimation and the FVS carbon reports website for more information and resources on FVS (USDA Forest Service, 2022c).

5.2.1.2 Activity Data

For silvicultural practices, activity data typically define the area of intervention, the rate or degree of intervention (e.g., acres per year), land-use change, land cover change, or management activities. For small landowners, it may be possible to delineate an area of land cover change using simple distance measurements or with the aid of GPS. Surveyors' reports, maps, aerial imagery, online State/community/town geographic information systems (GIS), or online tools such as Google Earth (see appendix 5-A.1.1) may also provide this information.

For more complex land holdings where different interventions are planned across noncontiguous land areas (several forest patches), or where land area is made up of a heterogenous set of characteristics such as soil type, vegetation cover, and disturbance history, it may be necessary to stratify the land into homogenous stands (see stratification discussion in section 5.1.5.1). Remote sensing or aerial photography (as simple as using Google maps or local/State GIS web portals) can be useful for any landowner, but they are especially useful for larger land units. Even where a single type of silvicultural activity is being considered, there might be a need to stratify based on conditions and species compositions. For example, a landowner may want to extend the rotation time for two different stand types on their property: a Douglas fir/ponderosa pine stand and a lodgepole pine stand. Having species-specific activity data allows for the application of species-specific emission or removal factors, rendering potentially more accurate quantification outputs.

Equally important, but beyond the basic management interventions outlined in section 5.2.1.1, a forest holding may also have a variety of complex interventions comingled across space and time for which a Level 3 approach may require advanced FVS customization of management specifications in order to estimate GHG results (Hoover and Rebain, 2011). In many cases, landowners will have estimates of land area and management objective readily available for use as activity data. For example, they may already have an estimate of the area of land they wish to reforest, which they defined using a standard GPS device. In other cases, due to the size of the property or the heterogenous nature of the land cover, measurement using a GPS device or Google Earth may be less practical. In those cases, there are online tools that may offer a cost-effective way to stratify land and quantify the area in which a silvicultural intervention can take place (i-Tree, 2022a). See appendix 5-A for a description of how to use i-Tree Canopy or Google Earth for estimating the area of each stratum.

Tools and online software platforms are continuously emerging to support entity-scale decision making around climate-smart forestry and policies. These combine GIS mapping and interactive maps to produce custom estimates of forest carbon flux. One such tool is the Measurement Reporting and Verification (MRV) Toolkit (https://www.goeslab.us/forest-carbon-mrv-tool.html), developed by Michigan State University. It is designed to support users in developing site-specific emission or removal factors from forest inventories and combine them with activity data to render estimates of GHG flux from forest management practices. It offers a library of tree volume/biomass equations and activity data from remote sensing or land-use change data. Using these data, the MRV Toolkit estimates emissions and carbon removals for a selection of land use and silviculture situations or scenarios, either as a single practice or as a sequence of linked practices. It supports a complete statistical allocation of a field-based sample plot frame for a forest inventory, or a more simplified use of default values that circumvents the need for a more resource-intensive forest inventory. Appendix 5-A.6 provides carbon estimation tools and data sources.

5.2.1.3 Limitations and Uncertainty

Limitations

The Level 1 approach offered in this section does not fully cover the breadth of silvicultural practices entity owners might seek to adopt. The diversity of traditional silvicultural practices and emerging techniques for enhancing forest resilience and ecosystem service provision, combined with the innumerable combinations of vegetation, climate, and site conditions found across the United States, presents significant challenges in providing consistent and broadly accessible ways to credibly estimate GHG flux.

The selection of variables used to group FIA plots for the Level 1 analysis does not fully account for the impact of management practices within silviculture. While FIA offers a rich source of data on forest stand attributes, and remeasurement of plots allows for the quantification of carbon stock change, the impacts of specific management practices are harder to assess. A more robust modeling approach is needed for these purposes but is beyond the scope of this version of the report.

Additionally, site conditions at time 0 for many forest management operations can be important for subsequent forest regrowth and carbon accumulation, but they vary widely, and the Excel workbook currently does not allow the addition of site classification variables. Further research is needed to build a more robust modeling platform and approach for understanding the impact of a broader set of management interventions on contemporary forest carbon dynamics.

Future iterations of this guidance will continue to bring in the best science and attempt to present it in a manner that enables climate-smart decision making for a broad range of users. Emerging online tools, forest modeling advancements, and advances in carbon accounting approaches will continue to provide solutions to today's accounting barriers.

The calculations proposed for this section and section 5.2.2, along with associated data inputs, characterize a large portion of the journey carbon takes from the forest ecosystem back to the atmosphere; however, they are incomplete. The methods provide an approach for estimating carbon that is sequestered in a forest through growth, with additional carbon being potentially sequestered by a limited set of forest management interventions. They also provide an estimate of potential emissions from logging residues left on site after harvesting, but these estimates are based on a broad national default wood utilization rate. Section 5.2.2 accounts for the rest of the carbon's journey though wood products in use and in SWDS. Always consider the full journey of carbon through both the ecosystem side and the HWP side for complete accounting.

There remain notable gaps in the accounting due to a lack of existing data and research to draw from. These include, but are not limited to:

- Connections between known harvest volumes/wood mass (across a range of tree sizes, species, and quality) and the HWP calculations. This includes the application of default values from Smith et al. (2006) and Johnson (2001) that may not reflect contemporary forest management, harvesting, and mill practices.
- Emissions-at-harvest estimates, which need further refinement to reflect the diversity of wood utilization outcomes of harvest.
- Modeling various forest management practices and postharvest growth across the different forest ecosystems. This persistent research need can be met using biometric models such as FVS as part of Level 3 approaches.

- Better understanding of the impacts forest management and harvest equipment have on soil carbon stocks.
- Better estimation/modeling of the lateral transfer of carbon between live tree and standing/down dead tree pools. As the official U.S. forest inventory is used to estimate carbon dynamics associated with the Level 1 approach in this guidance, refined alignment between fixed-area sample plots for standing trees and line-intersect sampling for down dead trees is needed.
- Refined estimates of forest carbon pools beyond aboveground live trees such as DDW, understory vegetation, belowground carbon roots associated with live/standing trees and stumps, and soils/litter. In particular, while soil is the largest stock of carbon in forest ecosystems, current FIA sampling density and frequency limit the ability to characterize soil carbon change. As such, soil carbon was a carbon pool omitted from the default tables.
- Climate change impacts on tree growth and disturbance likelihood (e.g., wildland fire, insects and disease).

These are active areas of research, the results of which may be important to incorporate in future versions of these guidelines. See appendix 5-C for a more complete exploration of research gaps.

Uncertainty

There are many sources of uncertainty associated with estimating the carbon impacts of silvicultural systems, such as the compounding of errors associated with the estimates of carbon stocks across a diversity of pools, stand structures, species compositions, and site qualities subsequent to management actions. Perhaps the largest source of uncertainty is the application of carbon stock and growth factor lookup tables partitioned with a relatively small number of classification variables to a specific stand.

The development of methods for estimating uncertainty of estimates applied to small areas is an active area of research. If plots are collected within the stand being assessed, standard uncertainty estimation techniques apply. However, if there are no plots in the area of interest, model-based approaches are commonly used, and generating uncertainty estimates from model outputs is challenging.

In addition, the estimation of non-CO_2 GHG fluxes is very uncertain and must be used with some degree of caution. This is especially true for N_2O in all activities and CH_4 in forest establishment. Considerably more research is needed in this area.

Another uncertainty in most estimates is the fraction of standing dead biomass. Based on previous work (Woodall and Monleon, 2008), it is believed to be small, but the variation with forest types, stand age, conditions, and activities is large. With default values, this may be a challenge to the final estimation. If direct measurements are to be made on site, the standing dead can be measured along with standing live biomass. This approach may have special benefit if the site being cleared has been intensely damaged by pests or disease.

The computation of whole tree biomass from allometry is another challenging source of uncertainty. There is literature on allometry for North American tree stem volumes and biomass, but less on whole tree volume and biomass. The updated NSVB estimators (Westfall et al., 2023), adopted by the FIA program in September 2023, are integrated into the lookup table values in the accompanying Excel workbook. These data are based on actual tree measurements and offer many advantages in terms of lowering uncertainty and better reflecting whole tree biomass as compared to the former component ratio method (Woodall et al., 2011). However, no estimate of uncertainty is offered in this guidance under the Level 1 approach.

This may be important because most landowners will not have the ability or interest to conduct their own destructive tree sampling to extract local whole tree biomass allometry (i.e., an IPCC Tier 3 approach). Beyond aboveground live tree carbon estimates, there can be even greater uncertainty associated with the additional ecosystem components of standing dead trees, soils/litter, belowground pools associated with live and dead trees, and DDW. Proper accounting for changes in these forest carbon pools is needed to reduce uncertainties associated with forest carbon dynamics, especially in the context of natural disturbances and management actions (sometimes comingled across space and time).

In conclusion, the Excel workbook and the treatment of silvicultural activities in this guidance do not give a full accounting of carbon dynamics resulting from forest management. A number of simplifying assumptions were made, such as carbon neutrality pretreatment (in the case of reforestation) or post-treatment (in the case of extended rotation and harvest). Furthermore, certain carbon components found in the FIA-derived lookup tables, such as transition of standing dead trees to the DDW pool, are not measured directly but inferred through model outputs. These assumptions and gaps in the accounting balance sheet add to uncertainty but are actively being addressed with new research and modelling approaches.

5.2.2 Harvested Wood Products

Method for Estimating Carbon Storage and Emissions and LCA-Quantified Substitution Impacts From HWPs

Production Approach (for Stocks of Carbon Stored in HWPs)

- For Level 1, the Excel workbook computes results using basic user inputs. It applies the IPCC-guided production approach of HWP carbon accounting, in which carbon contained in wood and wood products remains in the account of the producing entity regardless of where the wood or wood product is used (Brown et al., 1998).
- This approach is broadly applicable, but the numeric tables and other values are unique to U.S. applications for estimating the annual changes in carbon stocks in products in use and in SWDS as well as the annual carbon emissions to the atmosphere.
- Use the Excel workbook to estimate the amount of HWP carbon from the current year's harvest that will be stored in the HWP pool over the next 100 years.
- Two decay functions are available to model products in use lifespans before disposal: the more traditional "exponential" function and a novel alternate "chi-square, gamma" function. The latter is the default function applied in the Excel workbook but users can also obtain results from using the traditional "exponential" function.

LCA Approach (for HWP GHG Emission and Substitution Impacts)

- For Level 1, the Excel workbook computes results using basic user inputs. It applies the LCA method to quantify GHG emissions for HWPs as kg CO_2-eq emitted per kg of an HWP on an oven-dry basis. The LCA approach is guided by the ISO 14040 and 14044 standards.
- The quantification of GHG emissions in this guidance refers to cradle-to-gate LCA, which includes life stages of HWPs from forest harvesting to product manufacturing.
- The HWP substitution factor lookup tables are based on the GHG emissions avoided when substituting wood for nonwood products in a functional equivalent application.

- The substitution factors are provided to help forest landowners quantify and compare the carbon emission impacts/benefits from the wood harvested for different products and applications as a substitution for potentially higher-GHG-emitting activities outside the forest system boundary, such as the use of concrete and steel in construction. The potential substitution calculator built into the Excel workbook uses lookup tables to estimate the average amount of potential GHG emission reductions through the substitution by HWPs from the current year's harvest.

When landowners conduct forestry operations, they often cut trees. In some cases, they cut all or nearly all trees in a stand; in others they cut only specific species, sizes, or combinations of trees. During harvest operations, trees are delimbed before or after skidding to landings, stacked, and then loaded onto trucks/trains for transport to wood processing facilities, where they are used as either sawlogs or pulpwood. Fuelwood is often taken to homes or retail operations. Some cut trees and associated slash remain in the forest after harvest.

To understand the net environmental impact of HWPs, one needs a clear understanding of the emissions associated with production of the wood products, along with their longevity across space and time (see figure 5-2). The production approach aids in understanding carbon storage and the longevity of storage. The longer the biogenic carbon in HWPs stays in a sequestered form, the more significant are the environmental benefits associated with the wood product under consideration (Lippke et al., 2011; Ganguly et al., 2020). However, these biogenic carbon storage benefits need to be compared against the fossil emissions associated with the harvest and manufacturing of these wood products, which can vary significantly among the wood products (Sathre and O'Connor, 2010; Ganguly et al., 2020). The LCA approach discussed here quantifies the holistic fossil fuel emissions during the harvesting, transportation, and manufacturing processes.

It is important to understand how the types of woody material left behind after harvesting affect the two HWP approaches. Cut trees left on site transition from the live standing ecosystem pool to the dead and downed pool, with potential transfer to the soil carbon pool as they decay; most stored carbon in these pools is eventually emitted to the atmosphere over time. Likewise, when loggers harvest a tree, they often leave some parts of it on site, including tops, branches, stump, roots, and sometimes bark. Landowners/foresters are advised to manage this woody material (biomass) to comply with fuel management regulations often established by jurisdictions (e.g., towns, counties, or the State) or by State Foresters. Foresters often pile the remaining woody materials and allow them to dry out before burning them without energy capture when wildfire is not a threat. In many cases foresters also conduct a prescribed fire at the harvest site to reduce dangerous fuel loads and to prepare the site for reforestation.

An approach to quantify the emissions associated with this woody material left on site postharvest is provided in section 5.2.1 (equation 5-3)(and is included as an output in the Excel workbook in the "Forest Management & HWP Results" tab in the green "Ecosystem Carbon Impacts" area of the tab).

Central to dealing with wood products in carbon emission inventories is recognition that when a forest is harvested, all of the sequestered carbon is not immediately released to the atmosphere. Some is released across century-long time scales. Some will be retained in wood products and in landfills and released to the atmosphere mainly as CO_2 but also as CH_4 over time (this guidance does not include associated methane emissions). Some carbon will be retained in perpetuity in landfills.[8] Once logs arrive at processing facilities, there are four general stages for the loss of carbon from wood products (Skog, 2001):

1. Processing roundwood to produce primary wood products.
2. Fabricating primary wood products into end uses.
3. Discarding products in use over time, with some burned, recycled, sent to landfills, or taken to secondary uses including recycling which can extend the carbon-in-use lifetime.
4. Decaying over time in landfills.

Other portions of this chapter discuss the amount of wood carbon that is released as CO_2 during the three processing stages (i.e., roundwood to primary products, primary products to finished products, and disposition of products at the end of their useful lives). This section deals with the amount of carbon that is released over time, up to decades and centuries, as products in use and products in landfills are burned or otherwise oxidized to CO_2.

Note that accounting for CO_2 emissions over time can be very different at a national or regional level than at the level of a smaller entity (e.g., Stockmann et al., 2012). For example, Skog and Nicholson (2000) estimate at the national level how the stock of carbon in wood products has evolved over the years and accumulated over time—tracking inputs to and outputs from carbon pools during each accounting year. Smaller-entity accounting deals with the anticipated decay of products and the release of carbon over time from a single harvest event or projection.

5.2.2.1 Description of Methods

This section describes the main approaches that entities and researchers currently use to quantify carbon storage and GHG emissions from HWPs: the production approach and the LCA approach. Given the complexity of available methods, tools, and models for quantifying carbon storage and other GHG impacts of HWPs, this section provides Level 1 versions of these approaches, though existing tools are referenced where more accurate estimates could be rendered. Level 1 approaches rely on the accompanying Excel workbook to combine built-in calculators with preprocessed values in lookup tables with basic user inputs to render region- and forest-type-specific values for the amount of carbon stored in products in use and in landfills and associated emissions.

Outputs from this section can be combined with the outputs from section 5.2.1 (converted from per area to total storage and emissions estimates) to develop a more complete understanding of GHG fluxes from forest management activities. The Excel workbook demonstrates how outputs from ecosystem and HWP modeling are combined, where all wood removed for wood products is converted into emissions or storage. Storage in HWP represents a transfer within the forest sector from ecosystem pools to HWP pools (both products in use and SWDS). Emissions include logging residues and bark (assumed to be immediately emitted from the ecosystem pools), emissions via processing in the year of harvest, and discarded product emissions (including burning and partial decay in landfills, which are all considered HWP emissions).

This method estimates carbon additions to the stock of HWPs from trees forest landowners harvest or when they have harvested or are contemplating harvest. The accounting framework used to track HWP carbon is similar to the framework that the UN reporting nations (including the United

[8] Dumps were not considered for the discarded wood products as the latest EPA waste reduction model (WARM) data suggests HWPs are no longer disposed of in dumps.

States) use to report national-level annual changes in HWP carbon stocks under the United Nations Framework Convention on Climate Change (UNFCCC).

The national accounting framework and these methods adopt the production approach: (1) tracking carbon in wood that was harvested in the United States (IPCC, 2006, 2019); (2) providing estimates that track wood carbon held in products, even if the products are exported to other countries; and (3) estimating the overall stocks and annual carbon additions to and removals from the stock of carbon stored in wood products in use and in landfills.

Note that use of the production approach to accounting is not an LCA that could evaluate the total potential environmental impacts of a product (or services) through its entire life cycle (an attributional LCA) and how environmental impacts change if increased wood burning or increased use of wood products to offset more fossil fuel emissions and emissions from making nonwood products over time (a consequential LCA; see appendix 5-B.2.3). The estimates of annual change in carbon in HWPs are not intended to indicate the total impact on GHG levels in the atmosphere of using HWPs (including use of wood for energy), nor are they intended to indicate that the emission to the atmosphere took place in the United States vs. other countries where products were exported. They are intended to model subnational entity carbon storage, essentially mirroring national-level UNFCCC reporting methodologies at a smaller scale.

The production approach acknowledges that harvesting of forests does not immediately release all the forest carbon to the atmosphere; the approach counts only the biogenic carbon change (stocks and emissions) for the HWP pool to allow annual carbon changes in HWPs to be deducted from or added to ecosystem changes; as a result, it is clear what happens in both the ecosystem and HWP pools. However, while the IPCC reporting keeps these separate—so there will be no omission or double-counting of sequestration or emissions to the atmosphere—these guidelines take the additional step of combining the estimates to demonstrate how harvesting simultaneously impacts both pools by transferring some carbon from ecosystem pools to HWP inputs.

In the national accounting framework, the annual emissions from wood energy are accounted for as emissions with energy capture. The remainder of energy emissions occur in other sectors. IPCC does not explicitly quantify the displacement of nonwood energy options when fuelwood and harvested wood products in use are disposed by burning with energy capture (i.e., wood energy). However, as part of the modeling approach in this chapter, the annual HWP emission estimates from wood energy, which are part of the aggregated annual change in forest (ecosystem plus HWP) carbon pools, are brought into a different potential substitution calculator that shows the amount of emissions displacement when wood burning displaces four common heating fuels. So, while wood energy displacement is not included in the production approach here, to ensure there is no omission or double counting of sequestration or emissions to the atmosphere, which user is instead provided potential substitution estimates to consider the impacts HWP wood energy has on the energy, manufacturing, and waste sectors.

Level 1: Production Approach

The Excel workbook combines user-provided activity data with built in calculators that estimate the carbon HWP stocks for the “Basic projection under fm, with harvest,” “Harvest,” and “Extended rotation” forest management activities. There are three calculators:

- The growing stock calculator
- The harvested wood storage calculator (abbreviated to “harvest carbon calculator” in this chapter)

- The potential substitution calculator

They work together to render results that are ultimately presented in the "Forest Management & HWP Results" tab of the Excel workbook.

Table 5-7 describes the required data inputs to apply the Level 1 production approach, as well as some caveats.

Table 5-7. HWP User Data for the Accompanying Excel Workbook

Data Input	Description/How Data Are Sourced/Relevance	Required?
Type of forest management treatment applied	Select one of the various types of forest management treatment to model. Note that the "harvest" scenario will not include quantified results for the forest management practices, as harvest is assumed to occur immediately after time 0. Harvest outputs are combined with the harvest carbon calculator outputs.	Yes
Area subject to management activity or area of stratum	Harvest area (either as hectares or acres). This is used to produce an estimated default growing stock value. Alternatively, if known, harvest volume or weight of up to three different products can be entered using a range of units—MBF (thousand board feet), CCF (hundred cubic feet), green tons, dry tons.	Yes
Area units	Enter acres or hectares.	Yes
U.S. region	The broad geographic region in which the HWP activity takes place. See figure 5-4 for a map of how the geographic regions are delineated.	Yes
Forest type group	Enter the forest type that best matches the forest stand (not the species of wood cut). Choose "unknown" if the forest type is not known.	Yes, if harvest volumes are not known
Planted or natural forest origin	Select whether the forest was planted or of natural origin. Choose "unknown" if the stand origin is not known.	Yes, if harvest volumes are not known

Data Input	Description/How Data Are Sourced/Relevance	Required?
Age class	Enter estimated age class of the stand (in 20-year classes up to 100-plus). Choose "unknown" if the age class is not known.	Yes, if harvest volumes are not known
Years until harvest	For forest management treatments that have a harvest, enter the years from now until harvest under the baseline (0–50, in 5-year classes up to 50). For extended rotation forest management treatments that have a harvest, enter the years until harvest under extended rotation (0–50, in 5-year classes up to 50).	Yes, if extended rotation
Harvest volume known	If the amount harvested, or to be harvested, is known, choose "yes." This option bypasses the growing stock calculator.	No
Percent of the "area subject to management activity" to be harvested	If the entire "area subject to management activity" will not be harvested, enter the estimated percentage that will be harvested. For extended rotation activities that are assumed to be done in even-aged stands, this value defaults to 100 percent.	Yes
Harvest amount	Enter the numerical harvest value for up to three products.	Yes, if user-defined harvest data
Units	Enter the appropriate total or per area units.	Yes, if user- defined harvest data
Wood type	Enter "softwood," "hardwood," or "unknown" for up to three products.	No
Timber product	Enter the timber product type as sawlogs, pulpwood, or fuelwood. Choose "unknown" if the timber product type is not known.	No
Harvest fuelwood	Enter known fuelwood data. Use the default for any fuelwood for which data are unknown. Choose "no" if fuelwood was not part of the harvest amount.	No

Data Input	Description/How Data Are Sourced/Relevance	Required?
Fuelwood addition	Yes (default) or no to adding fuelwood to sawlog and/or pulpwood harvest amounts, based on what was removed from the forest.	No

Box 5-8. Key Definitions From Johnson (2001), Used by Smith et al. (2006) and in the Excel Workbook Calculators

Growing stock removals: The growing stock volume removed from poletimber and sawtimber trees in the timberland inventory. Includes volume removed for roundwood products, logging residues, and other removals.

- **Growing stock volume.** The cubic-foot volume of sound wood in growing stock trees with 5.0 inches dbh or larger, measured from a 1-foot stump to a minimum 4.0-inch top diameter of the central stem (outside bark).
- **Logging residues.** The unused merchantable portion of growing stock trees cut or destroyed during logging.
- **Sawtimber-size trees.** Softwoods 9.0 inches dbh and larger; hardwoods 11.0 inches dbh and larger.
- **Poletimber-size trees.** Softwoods 5.0 to 8.9 inches dbh; hardwoods 5.0 to 10.9 inches dbh.

Nongrowing stock sources: The net volume removed from the nongrowing stock portions of poletimber and sawtimber trees (stumps, tops, limbs, cull sections of central stem) and from any portion of a rough, rotten, sapling, dead, or non-forest tree.

Sawtimber volume: Growing stock volume in the sawlog portion of sawtimber-sized trees in board feet (international ¼-inch rule).

Pulpwood: A roundwood product that will be reduced to individual wood fibers by chemical or mechanical means. The fibers are used to make a broad generic group of pulp products that includes paper products and other engineered wood composites.

Fuelwood production: The volume of roundwood harvested to produce some form of energy (e.g., heat, steam) in residential, industrial, or institutional settings or public utilities; does not include derivatives of sawlogs or pulpwood used as fuel, called "fuel and other emissions primary products."

Growing Stock Calculator

The growing stock calculator applies user inputs to query the FIADB (Burrill et al., 2021) and Smith et al. (2006) tables and ultimately estimates the harvest volumes by roundwood product types.

To use the calculator, enter data or select from dropdown menus in the "User Data Entry" tab of the Excel workbook.

1. Enter basic inputs:
    a. Enter the type of forest management treatment applied (options that will generate HWP results from growing stock are "Basic project under fm, with harvest," "Harvest," and "Extended rotation."
    b. Enter an estimate of harvest area and choose units (acres or hectares).

c. Select U.S. region, forest type group, planted or natural forest stand origin, and age class.

2. Enter silviculture and harvesting inputs:

   a. Enter how many years from now until harvest.

   b. Enter "Yes" or "No" to the question, "Do you know what your harvest volume is?"

   If the volume is unknown, the growing stock calculator applies default estimates of growing stock (rendered from the FIADB net medium and large commercial volume and adjusted with Smith et al., 2006, lookup tables). If the volume is known, first enter the percent of the area subject to management activity from 1 to 100 percent. This reduces the growing stock subject to harvest using a percent. This could represent a reduction in areal extent (e.g., cut 80 percent of the forest area, leaving some areas uncut) or in the intensity of the harvest (e.g., cut 50 percent of the growing stock in the entire area). This reduction is not applied for extended rotation harvest, which assumes 100 percent is cut at the year entered for extended harvest.

   Then enter harvest amounts for up to three products with totals or, with per-acre values, the type of wood to be cut and sent to processing (softwood or hardwood) and the timber product category (sawlogs, pulpwood, or fuelwood), if known. If wood type or harvest information is not known, choose "unknown" and the calculator will use regional averages. Providing more details will yield more accurate estimates. Ensure all data, including total acreage, are put into the correct locations and units. Units for volume include MBF, CCF, green tons, and dry tons or cords.

   While using data from the table specific to forest type can improve modeling accuracy, note that these tables assume certain ratios of logs would come from certain species mixes, which may not accurately reflect a given landowner's harvest from their growing stock.

   The workbook will use the estimates to determine the total CCF equivalent of harvested roundwood.

   c. Determine if default fuelwood values should be applied.

      i. If sawlog and pulpwood production is not expected, select "No."

      ii. If unknown or if fuelwood data were previously entered, select "Yes." This adds fuelwood based on ratios from table 5B-3, unless fuelwood is any of the three indicated products. The results are harvest projections for use in the harvest carbon calculator (described below). Note that harvest projections may be greater than growing stock data entered because (1) roundwood yield is greater than 1.0 for growing stock in some regions and wood types and (2) fuelwood is added by default to sawlog and pulpwood volumes using default factors.

The calculator estimates the associated harvest volumes by product types using five pieces of information available by region (Smith et al., 2006):

- Averages for fraction of growing stock that is softwood/hardwood.
- Fraction of growing stock that is sawtimber size (table 5B-2).
- Fraction of growing stock volume that is roundwood—i.e., ratio of roundwood growing stock removals to total growing stock removals (roundwood + logging residues) (table 5B-3).
- Ratio of roundwood volume (excluding fuelwood) to total roundwood growing stock volume (including fuelwood) (table 5B-3).

- Ratio of fuelwood volume, from both growing stock and nongrowing stock sources, to total roundwood growing stock volume (including fuelwood) (table 5B-3).

The Smith et al. (2006) tables referenced above are included in appendix 5-B.2.2.

Harvest Carbon Calculator

The harvest carbon calculator automatically brings in the results from the "User Data Entry" tab. Total harvest units are determined by multiplying the user entered acres or hectares by the units entered on a per-area basis. The calculators currently use a ratio of 4.97 board feet per cubic foot (Verrill et al., 2004; gross board foot per net cubic foot ratio from 455,832 trees), which translates to 2.01 CCF per MBF; this may be adjusted in future versions to account for region, species taper, size classes, etc.

For CCF volumes, no conversion is needed. Volumes entered with MBF are multiplied by the ratio of CCF per MBF. Weights entered as dry tons are divided by the specific gravities (Smith et al., 2006) that correspond to the wood type and forest type in each region, then multiplied by 62.4 pounds per cubic foot, divided by 100 to get pounds per CCF, and then divided by 2,000 to get a CCF per ton. The CCF per ton conversion is used to compute CCF equivalents. For green ton weights, the calculator uses the same approach but also multiplies the CCF per ton by the appropriate average dry log weight relative to wet log weight for softwood (0.49) or hardwood (0.55) (Forest Products Laboratory, 2021).

The harvest carbon calculator relies on different proportions for sawlogs and pulpwood from table D6 of Smith et al. (2006) (table 5B-4) to allocate harvested wood in CCF equivalents into the full set of primary products in CCF units, using primary product ratios. For example, in the first row of table 5B-4, 0.391 of softwood sawlogs in the Northeast become softwood lumber, 0.004 become softwood plywood, etc. Note that 0.431 become fuel and other; across all rows, substantial portions of logs are converted to this coproduct, some of which is burned at the mill site to reduce energy needs to process the primary products. These portions are represented in the final column of table 5B-4 as "Fuel and Other Emissions," which is emitted at year 0—in other words, the year of harvest.

Fuelwood can be entered by volume or weight, or the default calculator will use table 5B-3's ratios of fuelwood to growing stock volume that is roundwood to estimate fuelwood using regional averages (ranging from 0.019 to 3.165) relative to the entered sawlog/pulpwood harvest or what the calculator derived from growing stock. Fuelwood is assumed to be burned with energy capture at the year of harvest, so it does not actually enter the products-in-use subpool; however, it is included in HWP emission estimates at year 0.

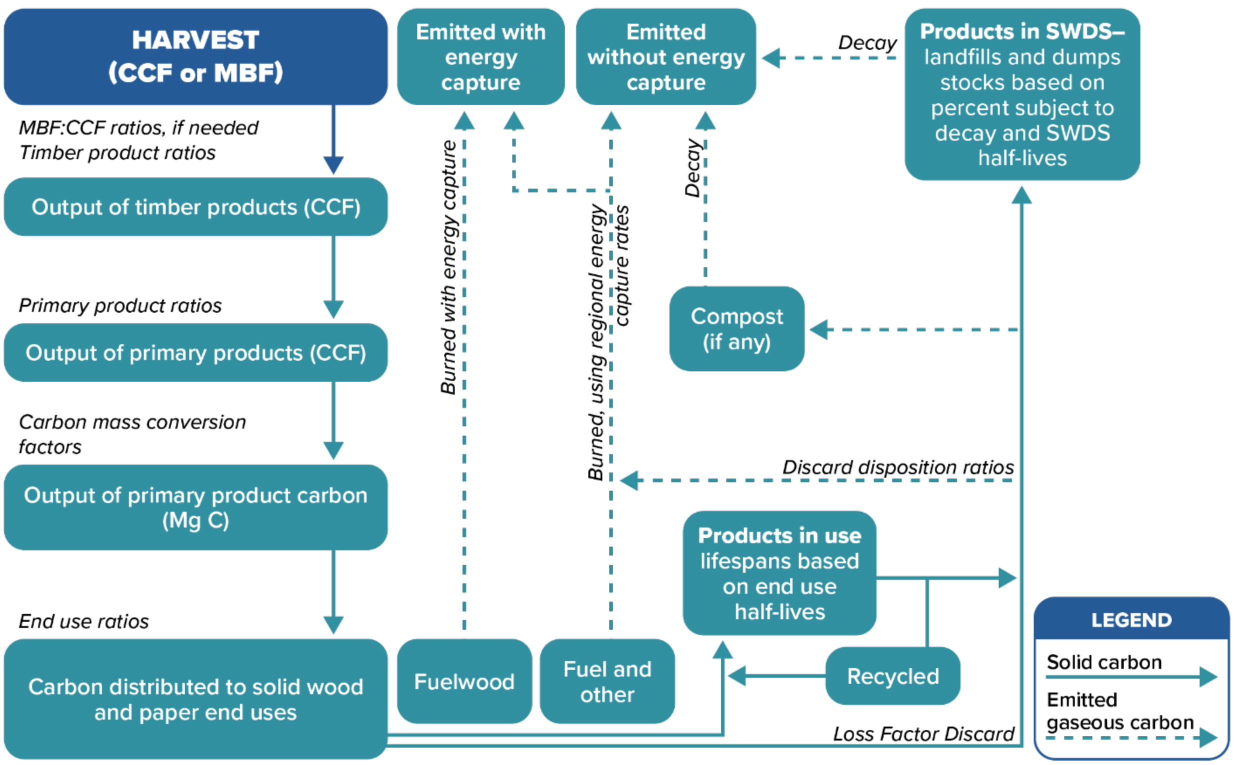
The calculator performs a series of conversions which differ slightly depending on if the inputs are softwood or hardwood and by forest type, by region. The calculator converts the CCF allocated to each primary product and coproducts into carbon mass by:

1. Accounting for density of wood relative to water using specific gravities for hardwood and softwood in each regions' forest type group
2. Converting 1 cubic foot of dry wood to pounds by multiplying density by 62.4 pounds per cubic foot
3. Dividing pounds into tons, then
4. Multiplying the dry CCF with the IPCC-recommended carbon mass relative to dry wood mass (0.5)

5. Converting from U.S. tons to metric tons[9]
6. Multiplying this weight by 100 to convert a single cubic foot to CCF

The result is the metric tons or megagrams (Mg) of carbon mass found in the CCF for each primary product and coproduct.

At this point the calculator also estimates bark from sawlogs, pulpwood, and fuelwood. Carbon contained in bark is tracked but not reported as part of HWP stocks or emissions, following 2019 IPCC guidelines for HWP feedstock (underbark) (Rüter and Lundblad, 2019). Emissions with energy capture for all bark are, however, recognized as part of the substitution calculator described below (emissions for bark burned without energy capture are not used in the energy substitution calculator).



Note: Fuelwood and Fuel and other are primary products.

Figure 5-5. Flowchart of HWP Conversions and Allocation and Disposition Ratios Used to Estimate Annual Storage and Emissions

[9] 1 U.S. ton = 0.907185 metric ton.

Then the calculator takes the primary products and distributes them to the full range of end uses using national proportions (e.g., softwood lumber for multifamily home construction), then disposes of 5 percent of each solid wood end use as loss during installation (U.S. EPA, 2018). Next, the calculator models product lifespans by applying decay functions built with the half-lives (see appendix 5-B.2.2 for more detail) appropriate for the range of end uses to show the portions retained in the products-in-use pool for year 0 and each of the first 100 years. Then the model distributes the end uses that leave the products-in-use pool each year (5-percent losses at year 0 for solid wood product and annual losses thereafter for both paper and solid wood products) using the latest (2018 data reported in 2020) EPA WARM (U.S. EPA, 2020b) estimates for three disposition categories: reuse, landfills, and burned (compost was zero for both paper and solid wood products in 2018).

To handle the burned portion of the disposed products in use, the calculator applies results from a formula combining three regional softwood or hardwood coefficients and the year since harvest when they were disposed of from Smith et al. (2006) table D7 (based on Birdsey, 1996, pages 1–25, appendixes 2–4) to calculate the portions of disposed end use products burned with and without energy capture. Emissions with energy capture for all HWPs are used in the substitution calculator as well.

Next, the calculator sets aside two percentages of landfilled wood waste (88 percent for solid wood end uses (U.S. EPA, 2020b, table 6-6) and 44 percent for paper end uses (Smith et al., 2006)) as permanent storage and applies first-order decay functions (with half-lives specifically representing anaerobic landfill decay for solid wood and paper landfilled lifespans—of 29 and 14.5 years, respectively (de Silva Alves et al., 2000; Freed and Mintz, 2003)) to the portions of landfilled wood products subject to decay (U.S. EPA, 2020b), to show the proportions retained in the SWDS pool for year 0 and the next 100 years.

Subtracting the sum of these two portions from 1.0 results in the biogenic emissions for each year. Putting this all together reveals the annual stocks and stock changes, also called flux, a complete picture of storage and emissions through time. The calculator results show negative signs for sequestration in the ecosystem and positive numbers for movement between ecosystem and HWP storage subpools of the forest sector carbon. The forest sector stock change or flux is the net ecosystem exchange, including marginal sequestration from extended rotations when applicable, and logging residue and bark emissions, minus harvest, plus the change in HWP stocks (products in use and SWDS). The following section provides more detail on these steps as well as an emerging alternative approach to this part of the modeling.

Displacement factors for potential substitution benefits in reducing GHG emissions in construction and energy sectors are presented later, in table 5-10. These numbers are reported separately because they are part of the LCA approach explained below but are mentioned here to show the relationship between the two modeling approaches.

Primary Product End Use and Landfill Decay Tables

For HWPs, the Excel workbook uses decay functions to document the rate at which the carbon moves from the products-in-use pool to disposition. Decay functions are mathematical expressions in which the existing pool diminishes at a rate proportional to its current value and/or its age. In the workbook, decay functions are used for two separate applications.

First, the workbook uses decay functions to represent the rate at which wood products in use complete their useful lives and transition to disposal or reuse. Table 5-8 shows half-life estimates from Smith et al. (2006) for some end use groups and more recent numbers derived by following Skog (2008) table 8 for residential half-lives—escalated by roughly 2 years for every 20 years since 1940—as well as the percent loss when placed in use.

Table 5-8. Half-Lives and Loss When Placed in Use for Primary Product End Uses

End Use or Product	Half-life in Years	Loss When Placed In Use
New Residential Construction		
Single family	87.8	0.05
Multifamily	53.7	0.05
Mobile homes	12.0	0.05
Residential Upkeep and Improvement	26.1	0.05
New Nonresidential Construction		
All ex. Railroads	67.0	0.05
Railroad ties	12.0	0.05
Railcar repair	12.0	0.05
Manufacturing		
Household furniture	30.0	0.05
Commercial furniture	30.0	0.05
Other products	12.0	0.05
Shipping		
Wooden containers	6.0	0.05
Pallets	6.0	0.05
Dunnage, etc.	6.0	0.05
Other Uses for Lumber and Panels	12.0	0.05
Miscellaneous Products	12.0	0.05
Solidwood Exports	12.0	0.05
Paper	2.5	0

Source: Smith et al., 2006; Skog, 2008 (adapted from information in table 8).

Second, the workbook uses a set of decay functions to determine the rate at which the solid waste in landfills decays over time and releases some of the biogenic carbon back to the atmosphere. When the rate of "decay" (i.e., the percent of carbon leaving the pool over any interval) is the same over equal intervals of time, the decay function takes the shape of an exponential curve. This pattern of exponential decay is widely used for modeling natural processes (like decay of wood in a landfill), but wood products leaving their functional life may follow a more complicated pattern. Appendix 5-A.3 discusses some potential patterns (i.e., distributions) that would represent the decay rates of various wood products under consideration.

Conventional exponential functions in table 5-B-5 and table 5-B-6 in appendix 5-B.2.2, and new chi-square functions (workbook default) in table 5-B-8 and table 5-B-9, reflect the total of all end use wood carbon in each primary product category in the products-in-use pool and the solid waste disposal pool (end-of-life portion) with fractions remaining for the subsequent 100 years. The calculator shows 1 minus the sum of these two fractions, or the remainder of the carbon, as being emitted through the combination of burning and decay by each year. In this way, the Excel workbook estimates HWP storage by adding the carbon masses for each primary product category multiplied by the fractions of each primary product remaining in end uses and SWDS each year, and then estimates emissions by any given year as 1 minus the combined fractions. See an example of the chi-square functions in box 5-9.

Box 5-9. Harvest Carbon Calculator Calculation Examples

Softwood Lumber

At year 10, table 5-B-8 shows 0.859 of softwood lumber remain in products in use; table 5-B-9 shows 0.112 of softwood lumber carbon originally placed in SWDS remains at year 10. Therefore 0.971 (= 0.859 + 0.112) of the carbon originally stored in softwood lumber in year 0 remains and 0.029 (= 1 − 0.971) has been emitted.

Looking at year 100, 0.134 of softwood lumber remains in products in use and 0.644 remains stored in SWDS. The remainder, 1 − (0.134 + 0.644) = 0.222, has been emitted.

Northeast Wood Pulp

Northeast wood pulp decays more quickly but also has high recycling rates: by year 10, 0.829402 remains, with 0.402 in products in use and 0.427 in SWDS. The remaining 0.171, 1 − (0.402 + 0.427), has been emitted.

Note that there are minor rounding differences for the fractions shown in this example.

Emission tallies start with all the fuelwood and the fuel and other emissions from year 0. Then, starting in year 1, the calculator takes the original carbon mass for each primary product category and multiplies it by 1 minus the combined fractions remaining. All of the products are then summed for a results summary. This is then converted to metric tons CO_2-eq by multiplying by 3.67 (or 44/12, the ratio of the molecular weights of CO_2 and carbon). Because the calculator models a single harvest event (not a multi-year harvest record) the total end use carbon remaining and the total of all wood removed from the forest that remains stored both decline over time.

When "fuel and other" coproduct biogenic emissions are combined with these annual biogenic emissions from the disposed solid wood burning and landfill decay to estimate cumulative emissions by the listed year there are large amounts shown in year 0—the year of initial processing—followed by smaller amounts in later years.

Summary results are presented as CO_2-eq in the "Forest Management & HWP Results" tab and detailed annual results are presented in the "Harvest Carbon Calculator" tab of the accompanying Excel workbook. The harvest carbon calculator shows three sets of results. The first are chi-square results by year in t CO_2-eq, then exponential results by year and chi-square results (Mg). All tables start with zero in rows for years after harvest in the calculator output table and contain as total products-in-use carbon (Mg), total SWDS carbon (Mg), total HWP carbon storage (Mg), annual HWP carbon stock change (flux in Mg), percent of installed end uses remaining stored, percent of harvest log carbon (underbark) remaining stored, coproduct biogenic fuel and other emissions year of processing (Mg), fuelwood emissions year of harvest (Mg), cumulative end use emissions carbon by this year (Mg), cumulative end use emissions by this year (t CO_2-eq), annual HWP emissions with energy capture (t CO_2-eq), annual HWP emissions without energy capture (t CO_2-eq),cumulative emissions by this year (t CO_2-eq), and percent of HWP carbon emitted by this year.

Bark is also computed on this tab, although it is listed separately because it is not considered HWP stock or emissions under current IPCC roundwood (underbark) feedstock definitions (Rüter and Lundblad, 2019). However, some wood processing facilities in the United States use bark for products such as landscaping materials or energy production (Marcille et al., 2020).

See appendix 5-B.2 for a full description of this chapter's novel approach to producing decay functions using chi-square functions to represent the lifespans for solid wood products and as displayed in the Excel workbook as default results. Users may choose to render results using the traditional exponential decay functions as well.

Level 1: LCA Approach

LCA Quantification of HWP Emissions (Cradle to Gate, From Forest to Product Manufacturing Gate)

The LCA method described in this chapter focuses on the fossil-based GHG emissions reported as CO_2-eq; it leaves out biogenic carbon, which is reported separately within the LCA framework following ISO 21930. It uses information derived from LCA studies that covered stages from raw material extraction to product manufacturing (cradle-to-gate), guided by the framework and guidelines from ISO 14040 and ISO 14044. An example of the LCA method can be found in section 5-B.2.3. Table 5-9 provides the GHG emission factor (in metric tons CO_2-eq/metric ton of product) of each HWP produced from forest lands, based on the U.S. LCA studies. (Note that mass product units are all on a dry basis.) The values—averages for the United States and some U.S. regions—include fossil CO_2, all CH_4, and all N_2O emissions within the specified system boundary. The total fossil-based GHG emissions for HWP manufacturing, from cradle to manufacturing gate, can be quantified by multiplying the HWPs' mass with the LCA-determined emission factors summarized in table 5-9. The LCA-quantified HWP fossil emissions are used to derive the displacement factors for substitution benefits, as described in the following section.

Table 5-9. Life Cycle GHG Emissions for Cradle-To-Gate Manufacturing of HWPs (Metric Tons CO_2-eq/Metric Ton of HWP Produced)

HWP	U.S. Average	Pacific Northwest	Southeast	Inland Northwest	Northeast–North Central	Study References
Softwood lumber	0.161	0.131	0.167	0.241	0.108	Puettmann, 2020a, 2020b, 2020c, 2020d
Hardwood lumber	0.273	ND	ND	ND	0.273	Hubbard et al., 2020
Plywood	0.476	0.395	0.558	ND	ND	Puettmann, 2020e, 2020f
Oriented strandboard	0.391	ND	ND	ND	0.391	Puettmann, 2020g
Non-structural panels[a]	0.742	ND	ND	ND	ND	Puettmann and Salazar, 2019; Puettmann and Salazar, 2018; Puettmann et al., 2016
Other industrial products[b]	0.272	ND	ND	ND	ND	Alanya-Rosenbaum and Bergman, 2020

ND = No data.

[a] Non-structural panels include three HWPs (particleboard, medium-density fiberboard, and hardboard). The GHG emissions value is a weighted average of the three.

[b] GHG emissions for wood pallets were used as a reference for other industrial products.

Avoided Emissions or Emission Reductions from HWP Substitution

LCA-quantified GHG emissions for wood products can be compared to emissions for functionally equivalent nonwood products (e.g., concrete and steel) to find out the possible maximum substitution benefits. Similar comparisons can be made between wood-based energy and fossil-based energy (e.g., coal, heating oil, natural gas). Because the life cycle GHG emissions associated with wood product manufacturing are generally lower than emissions for functionally equivalent nonwood materials, substituting wood for high-emitting nonwood materials will result in reduced GHG emissions.

A displacement factor (DF) measures the GHG emissions avoided when wood is used instead of nonwood fossil or petroleum-based material. DFs are estimated by comparing the total GHG emission differences between wood and nonwood products and divided by the corresponding carbon content. The expression is shown in equation 5-7 (Sathre and O'Connor, 2010):

Equation 5-7: DF for HWP GHG Emission Reductions

$$DF = \frac{GHG_{\mathbf{nonwood}} - GHG_{\mathbf{wood}}}{Carbon_{\mathbf{wood}} - Carbon_{\mathbf{nonwood}}}$$

Where:

DF	=	displacement factor (dimensionless)
GHG_{wood},	=	GHG emissions for wood, obtained from LCA studies (CO_2-eq)
$GHG_{nonwood}$	=	GHG emissions for nonwood alternatives, obtained from LCA studies (CO_2-eq)
$Carbon_{wood}$,	=	amounts of carbon contained in wood material (CO_2-eq)
$Carbon_{nonwood}$	=	0, unless the nonwood material contains biogenic carbon (CO_2-eq)

Note that the denominator in equation 5-7 requires carbon contained in the wood to be expressed as CO_2-eq. Since the LCA results for HWPs provided GHG emissions per metric ton of the product (as shown in table 5-9), the numerator (GHG emissions) must be presented as CO_2-eq emissions from the CO_2-eq contained in the wood. Table 5-10 presents these converted values based on the average density and moisture levels of the HWPs for all the regions. Table 5-10 provides only rough estimates and examples for displacement factors based on the limited research studies. Gaps in this area have been identified and are expected to be addressed with future, refined estimates.

For the estimation of DFs, this chapter draws on data from various studies (Xu et al., 2021; Leturcq, 2020; Krajnc, 2015; Bergman et al., 2014). Data were insufficient to estimate DFs for some HWPs; in those cases, this chapter uses averaged DFs from published meta-analyses (Leskinen et al., 2018).

Landowners can interpret the DF as an estimated potential savings in GHG emissions (i.e., reduction benefit) from substituting wood products and woody biomass energy for functionally equivalent nonwood products and fossil/non-renewable energy sources (table 5-10 and table 5-11).

Table 5-10. DFs for Material Substitution: HWPs Against Nonwood Products

HWP	Functionally Equivalent Nonwood Product	DF (Metric Tons CO_2-eq Avoided/Metric Ton CO_2-eq in HWP Used)	Reference
Softwood lumber	One steel stud[a]	0.99	Adapted from Bergman et al. (2014)
Hardwood lumber	One steel door[a]	2.29	Adapted from Bergman et al. (2014)
Plywood	Structural construction materials	1.3	Leskinen et al. (2018)
Oriented strandboard	Structural construction materials	1.3	Leskinen et al. (2018)
Other industrial products	Non-structural construction materials	1.6	Leskinen et al. (2018)
Other industrial products	Non-construction use	1.2	Leskinen et al. (2018)

[a] GHG emissions for the galvanized steel manufacturing process were used for steel studs and steel doors (source: Cai et al., 2022).

Table 5-11. DFs for Energy Substitution: Woody Biomass Associated With HWP Harvest, Transportation, and Production Against Nonwood Fossil Energy and Heating Sources

HWP	DF (Metric Tons CO_2-eq Avoided/Metric Ton CO_2-eq in HWP Used)
Electricity[a]	
Mill residues	0.270[c]
Logging residues	0.267[c]
Softwood pulp	0.261[c]
Heat (Wood Fuel)[b]	
Coal	0.68[d]
Oil	0.57[d]
Natural gas	0.45[d]

[a] Emissions for grid-based electricity were taken from U.S. EPA (2018a) eGRID using the national average profile.

[b] The calorific value of wood chips at 30 percent moisture content (12.2 megajoules/kg) was used (Krajnc, 2015).

[c] DFs when the woody biomass generated electricity to displace the U.S. grid-based electricity (mix of fossil and renewable sources).

[d] DFs when wood fuel generated heat to displace the fossil fuel (coal, oil or natural gas) generated heat.

Calculation of Potential Substitution Benefits from the Construction and Energy Sectors

For construction product substitution benefits, estimates made using the harvest carbon calculator for primary product carbon masses can be used in the potential substitution calculator. The calculator takes the appropriate masses of HWPs produced, converts them to CO_2-eq (by multiplying metric tons by the molecular weight conversion, 44/12 or 3.67), and multiplies the result by the DFs shown in table 5-10. The result gives the landowner a sense of GHG emissions that could be avoided if the full mass of the HWP produced from their land is considered to substitute for those functionally equivalent nonwood products in construction or other use.

For energy substitution benefits, estimates made using the harvest carbon calculator for the limited set of fuelwood emissions (CO_2-eq), and bark emissions (CO_2-eq) at the year of harvesting and processing (year 0) can be multiplied by the DFs in table 5-11 for different options in substitution benefits:

- Most (~80 percent) of the fuel and other (hog fuel and other mill residue) coproduct is already captured in the DF calculations for the wood products and is therefore shown in the product portion of the potential substitution calculator.
- Energy from burning woody biomass is used to substitute for electricity; the electricity values shown in table 5-11 do reflect renewables as part of the production portfolio.
- Heat generated from burning wood fuel substitutes for three fossil-based heating sources: anthracite coal, heating oil, and natural gas.

The calculator's results represent the GHG emissions that could be avoided when woody biomass associated with HWPs produced from the landowner's land is substituted for fossil fuel heating or electricity use. (In other words, the potential substitution calculator makes a big assumption—that all wood used in construction and burned with energy capture in year 0 substitutes for nonwood alternatives.)

5.2.2.2 Activity Data

Because entities may have many different types of information to describe the amount of wood harvested to estimate carbon stocks in HWP, the Excel workbook accepts a range of activity data:

- Growing stock cutting (described in the "Growing Stock Calculator" section).
- Harvest volume estimates (hundred cubic feet or thousand board feet volume, weights in green or dry tons).
- Volume conversions.
- Volume to carbon conversions.
- Loss factors.

5.2.2.3 Limitations and Uncertainty

Limitations

<u>Level 1: Production Approach</u>

The starting point for estimating carbon storage is estimating carbon content by converting from the weight(s) or volume(s) growing or harvested. The first step is entering either growing stock or harvest volumes (or projections). This might seem like basic information, but landowners have a wide range of access to it. Something as simple as log scale vs. lumber scale, or total volume compared to sawlog or merchantable volume, can create confusion and lead to incorrect estimates. Landowners should ask questions, when they survey (cruise) or sell timber products, that will lead to known, high-quality inputs.

There are many averages and conversion factors strung together to complete HWP production approach modeling. Many of these conversion factors (e.g., MBF/CCF) are contingent on variables beyond the scope of the Level 1 approach. For example, species mixes, tree dimensions, sawmill minimum sizes, etc., can influence the conversion factors. Entities with a need for accuracy or precision beyond regional average single conversion factors may wish to model with other more advanced tools, conduct uncertainty analyses, or cite existing uncertainty analyses from various authors.

Emission estimates shown in section 5.2.2 are restricted to CO_2—they do not include CH_4 or other GHG emissions—but are nevertheless presented in units of metric tons CO_2-eq. The IPCC guidelines (2006) for national estimates of CO_2 GHG emissions released from wood products in landfills are not included in the emissions from the waste sector but are included in the HWP pool of the AFOLU sector. On the other hand, emissions of CH_4 from landfills are included in the waste sector and therefore not included in HWP pool. IPCC (2006) explains: "The outflow and oxidation data of HWP are much more uncertain than the input data and are likely to be underestimated, as a result a significant part of decay would not be identified and net additions to carbon held in HWP would be overestimated." Future versions of these guidelines may address the topic of HWP landfill methane production from an "entity perspective" when such calculations can be determined with more certainty.

A more detailed discussion of data sources and limitations for several conversion factors, wood utilization parameters, discard pathways, and decay rates is offered in Lucey et al. (in review).

Level 1: LCA Approach

The Level 1 DFs for HWPs in construction use are averages from data referenced in published meta-analysis reports (Hurmekoski et al., 2021; Leskinen et al., 2018; Sathre and O'Connor, 2010). Otherwise, the two specific substitution paths, defined for softwood lumber and hardwood lumber as shown in table 5-10, and the associated individual DFs were calculated for this chapter based on the available LCAs and substitution data. Additional individualized DFs are needed for better quantification of substitution benefits from HWP.

Also, the substitution calculator's estimates do not include emissions when primary product end use HWPs are disposed of by burning (about 16 percent of solid wood products and 6 percent of paper), which is reduced with energy capture ratios to just the portion burned with energy capture. This is because the system boundary for the provided DFs is cradle to gate and does not include use or disposal stages.

Regarding DF and substitution benefit, the LCA literature provides strong evidence that most wood-based products are associated with lower fossil-based emissions over the product's life cycle compared to functionally equivalent nonwood-based substitutes. A DF quantifies the reduction in emissions per unit of wood used in specific end-use applications. DF values also factor in the efficiency of biomass in decreasing GHG emissions, as they go down with increased wood use for the same amount of GHG emission reduction. This guidance calculates the substitution benefit for various wood product groups (softwood lumber, hardwood plywood, etc.) using a weighted average of various end-use-specific DF values. These substitution benefit values could be used to estimate the change in emissions compared to the current baseline practices.

Regarding interpretation of substitution benefits**,** the material substitution numbers used in this guidance can be used to analyze micro-level substitutions by examining the marginal change between individual products or processes. The substitution benefit numbers can also be used to analyze the meso-level substitutions by examining the marginal structural changes in society's production and consumption patterns between industries or sectors of the economy (Gustavsson and Sathre, 2011). These numbers are not intended for macro-level estimates, which would require a better understanding of the macroeconomic and landscape implications of large-scale wood-based (or nonwood-based) substitutions. In such macro-level substitution scenarios, direct and indirect market responses, and the interdependencies between the various industrial sectors, must be analyzed to understand the net impacts on the resultant GHG flows.

Uncertainty

Strict adherence to the *Inventory of U.S. Greenhouse Gas Emissions and Sinks* report (U.S. EPA, 2020a) would require Monte Carlo simulations with assumptions and probability distributions regarding uncertainty for HWP specified for key variables including:

- Fractions of sawlogs and pulpwood going to various primary products
- Fractions of primary products going to various end uses
- Half-lives for primary product end uses
- Rate at which products are discarded from each end use
- Fraction of discarded wood or paper that goes to landfills
- Fraction of wood or paper sent to landfills that is subject to decay
- Rate of decay in landfills of degradable wood/paper carbon

Such simulations are beyond the scope of the Level 1 calculators and are better handled with more advanced models.

For context, Stockmann et al. (2012) conducted an uncertainty analysis for their carbon storage estimates in the Northern Region of the National Forest System. They used triangular distributions with 18 variables; expert opinion determined variable distributions, which generally narrowed in more recent years. They found a 90-percent confidence interval of -26.7 to 31.2 percent difference from the mean. That uncertainty was for more than 100 years of harvest data, so uncertainty for a single year—such as that modeled with the tool described in this section—would likely be far less.

More research is needed to improve differentiation of the various rates at which solid wood products are discarded from uses such as pallets, railroad, railcars, and furniture. These are currently grouped into one category; differentiating them would refine estimates of average carbon stored when a landowner knows which primary wood products are made from the wood that is harvested from their land. Alternate, empirically verified curves for discard rates from end uses, particularly discards from housing, could improve estimates of average carbon stored.

Variability in the DFs of wood to nonwood product substitution and biomass energy to fossil energy substitution is unknown but expected to be large. Note that, for instance, the DF of 0.99 for softwood lumber was an average of 0.85 from the Southeast and 1.13 in the Northeast–North Central region. This is because of the difference in the LCA-quantified GHG emissions of lumber production in these two regions: 0.168 and 0.108 kg CO_2-eq per metric ton of softwood lumber, respectively, in the two regions. Having more data points from future studies in this field would help in estimating DFs (regional and U.S. average) with reduced uncertainties.

5.2.3 Wildfire and Prescribed Fire

Method for Estimating Emissions From Wildfire and Prescribed Fire

- There are two Levels available for this sector, depending on data availability and user resources.
- For Level 1, use the Excel workbook with lookup tables developed by combining FIADB data on stand structure and surface fuel loading with the Forest Vegetation Simulator with the Fire and Fuels Extension (FFE-FVS).
- For Level 3, use FFE-FVS, FOFEM, or Fuel and Fire Tools (FFT) to produce custom modeled fire and emission scenarios.

5.2.3.1 Description of Method

Wildland fires produce direct and indirect carbon emissions. The direct emissions are instantaneous GHGs produced from the combustion of live and dead fuels including foliage, litter, duff, down dead wood (DDW), and dead tree boles (central stem of a tree). The mass of emissions produced is directly proportional to the mass of fuel consumed by fire. The amount of combustion and emissions varies based on the quantity and arrangement of live and dead fuel on a site, forest type, fuel moisture, and weather, all of which influence intensity (Finney et al., 2003; Loehman et al., 2014; Prichard et al., 2022; Urbanski et al., 2022). Combustion releases more carbon-containing gases and particles when fuel conditions are dry, due to increased consumption of large woody fuels and duff. Surface fuels such as dead leaves, grasses, and needles are largely consumed during most fires even during relatively moist conditions. When fuel and weather conditions are extreme, surface fires can transition to the crowns, burning both live and dead foliage and fine branches on trees (Loehman et al., 2014); the consumption of live tree boles and large branches is typically minimal, though, even during crown fires (Johnson, 1992).

This section offers two Levels for estimating emissions from wildfire and prescribed fire.

Level 1 Approach

In the Level 1 approach, the Excel workbook combines activity data (i.e., an estimate of the area burned or to be burned) with an emission factor calculated based on fire severity, region (using the regions shown in figure 5-4), forest type (based on the table in table 5-B-11), flame length, and fuel moisture. Enter each into the Excel workbook.

The Excel workbook produces estimates of emissions for three fire activity scenarios, described in table 5-12: high-severity wildfire, moderate-severity wildfire, and low-severity wildfire/prescribed burn. To produce estimates for mixed-severity burns, distribute the burned area across the fire activity scenarios. Because many plots fall into each bin of fire severity, forest type, and region, the approach summarizes emissions to the 25th, 50th (median), and 75th percentiles.

Table 5-12. Fire Activity Scenarios

Fire Activity	Description
Low-severity wildfire/prescribed fire[a]	< 20% tree mortality
Moderate-severity wildfire	40–60% tree mortality
High-severity wildfire	>90% tree mortality

[a] Prescribed fires can be of varying severities, including high-severity crown fire, but many resemble the low-severity scenario.

Fire severity corresponds to the percentage of tree mortality (quantified with basal area per hectare), as shown in figure 5-6.

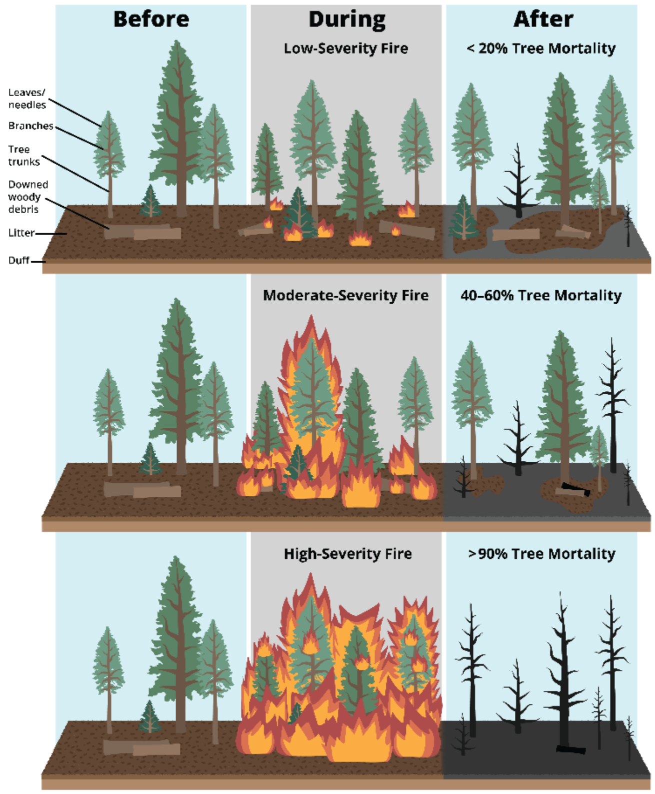


Figure 5-6. Diagram of the Three Fire Severity Levels for Which Level 1 Results Are Available

To estimate fire-induced GHG emissions and changes to carbon pools and vegetation under each of the scenarios described in table 5-12 for each forest type by region, the Level 1 approach combines:

- Estimates of initial (prefire) forest stand structure (species, size, number, and health of trees) and surface fuel loadings (DDW, litter, and duff), for different forest types and regions, from field measurements made by the FIA program.
- Simulations of fire under different flame lengths, fuel moistures, and weather conditions in FFE-FVS.
- FIA records the size (dbh and height of tree), status (live or dead), and species of each tree on its plots. FIA also measures litter and duff depth at eight points at each plot, as well as measuring DDW (e.g., branches and logs) along a set of transects; this information is stored in the DDW table (Burrill et al., 2018; USDA Forest Service, 2022b).

FVS is a forest growth model that simulates forest vegetation change in response to natural succession, disturbances, and management (Dixon, 2002); FFE simulates fuel dynamics, fire behavior, fuel consumption, and mortality due to fire (Rebain et al., 2021). FFE-FVS uses many of the same internal algorithms for estimating fuel consumption and emissions as the FOFEM model prescribed in the 2014 guidelines, as well as a similar tree mortality approach; unlike FOFEM, though, it can simulate stand, fuel, and carbon dynamics over time while also being able to incorporate FIADB (Burrill et al., 2021) plot data—that is, it is dynamically connected to contemporary forest resource information via FIA data. It is a powerful predictive tool, offering a more advanced means to simulate fire impacts than simpler algorithms such as those in the *2006 IPCC Guidelines for National GHG Inventories* (IPCC, 2006) while also enabling simulation of various management approaches (e.g., clear-cut vs. timber stand improvement activities). In totality, this approach facilitates connections among national databases, modeling/simulation tools, and region/forest type configurations while acknowledging much work remains in refining approaches to estimating probabilities of future fire occurrence, forest management activities, and fuel dynamics under global change scenarios.

FIA data from FVS-ready tables packaged with FIADB (Shaw and Gagnon, 2019) were used in FFE-FVS to establish prefire carbon pools and fuel loading for trees (live and dead), herbs and shrubs, woody fuels, litter, and duff (Crookston and Dixon, 2005) (see figure 5-1). FFE was then used to simulate immediate fire effects—tree mortality, fuel consumption, and changes in carbon pools resulting from three wildland fire scenarios (see table 5-12). GHG fire emissions are calculated as the product of fuel consumption from the FFE-FVS simulations and pollutant emission factors as described in appendix 5-B (see table 5B-12). Fuel consumption depends on fuel quantity, fuel properties (particle size, packing density, moisture content), weather, and fire behavior. The fraction of fuel consumed by fire can vary considerably across fuel strata (e.g., trees, litter, duff, and dead woody fuels; for example, a low-severity fire might consume 60 percent of the litter and 0 percent of the canopy fuel).

To determine the mortality levels of the fire severity scenarios, FFE simulations were run using a matrix of fire-related parameters (wind speed, fuel moisture, temperature, and burn patchiness). The mortality resulting from a given set of parameters can vary tremendously between forest stands. Region, forest type, and stand composition and structure are critical factors in stand mortality. Tree species and diameter are also important factors; for a given fire scenario, mortality may be highly variable across stands of the same forest type and region. Mortality simulation results were retained for creating estimates of GHG emissions and carbon pools (see table 5B-13).

FIA data from about 70,000 plots were processed with FFE-FVS to produce each of the fire severity scenarios. Because FVS is organized as a set of 20 regional variants, subsets of FIA plots were run using the variants in which they were located. FIA plots were attributed with FIA forest type and forest type group classifications (table 5B-11); the geographic regions depicted in figure 5-4 were assigned to FVS output by aggregating States and counties assigned to the regions. For the conterminous United States, over 350,000 combinations of region, forest type, and fire conditions were simulated. Appendix 5-B.3.2 provides more details on the simulation procedure.

Emissions of GHGs—including CO_2, N_2O, and CH_4—were calculated as the product of fuel consumption from the FFE-FVS simulations, using pollutant emission factors as described in chapter 2.

Estimates of fire effects and carbon were produced and aggregated into lookup tables based on forest type (table 5B-11), geographic region (figure 5-4), and fire severity (table 5-12):

- **FIRE table.** Immediate fire effects on the forest—biomass consumed, carbon emitted, carbon remaining, and GHG emissions.
- **CARBON table.** Prefire and immediate postfire carbon pool estimates.

The accompanying Excel workbook offers estimates of GHG emissions for the three fire severity scenarios based on user-provided information on area, region, and forest type. Figure 5-7 summarizes the method by which these estimates were produced.

See appendix 5-B.3.2 for details on the approach described above.

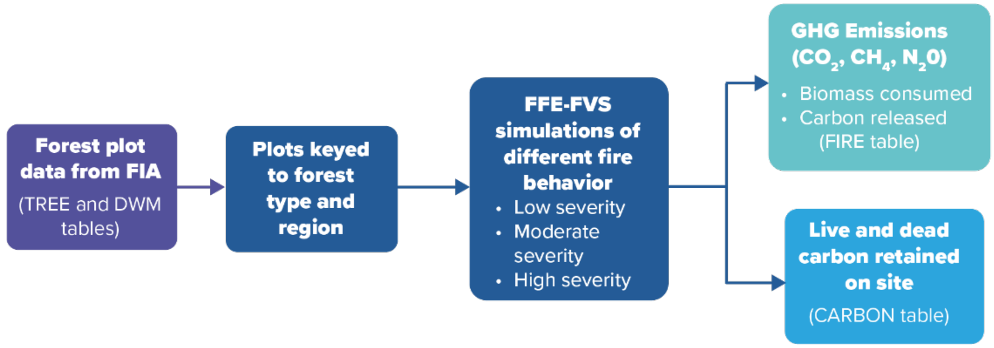


Figure 5-7. Diagram of the Wildfire Carbon Flux Method

Interpreting Results

The Excel workbook outputs present estimated emissions from fire according to the three scenarios in table 5-12. This approach is limited to immediate fire-induced GHG emissions and does not address postfire forest carbon fluxes such as the decay of fire-killed biomass. As a result, it is merely a potential starting point for assessing the forest carbon implications of fuel management treatments intended to improve forest health and reduce the risk of catastrophic wildfires.

These treatments can effectively reduce the severity of fires for a time, after which they may reduce the size of fires by reducing rates of spread and providing opportunities for fire suppression forces. However, their implications are complex—and the subject of ongoing research (Prichard et al., 2021; Thompson et al., 2017).

Level 3 Approach

For more advanced users, a number of options are available for estimating emissions from specific fire scenarios.

FFE-FVS (Rebain, 2010; Reinhardt and Crookston, 2003), used as part of the Level 1 approach, can also be used for custom model runs. FFE-FVS estimates tree mortality, fuel consumption, and emissions and simulates stand, fuel, and carbon dynamics over time. It is a powerful predictive tool, but using it for custom runs involves substantially more work in understanding the modeling framework, setting up runs, and preparing data.

Another option for advanced users is FOFEM (Reinhardt et al., 1997; Lutes, 2019), which is applicable nationally, has code that can be linked to or incorporated into other code, and defines inputs so that measured biomass can be entered or default values generated by vegetation type (USDA Forest Service, 2022d). FOFEM produces direct estimates of GHG CO_2 and CH_4, as well as estimates of fuel consumption by component, which can be used to determine residual fuel quantities for estimating subsequent decomposition. FOFEM can also be used to compute tree mortality in order to update estimates of live and dead biomass.

FFT, like FOFEM, can be used to directly compute emissions and fuel consumption from fire (USDA Forest Service, 2022e). FFT outputs include estimates of carbon stores for different fuelbeds, fire-induced carbon emissions, and fuel consumption. However, unlike FOFEM and FFE-FVS, FFT does not provide tree mortality estimates.

5.2.3.2 Activity Data

Activity data represent the area (in hectares or acres) in which the activity takes place—that is, the area burned.

5.2.3.3 Limitations and Uncertainty

Limitations

The methodology in this section does not quantify several aspects of carbon emissions and uptake by forest systems related to fire. It is limited to instantaneous emissions from fire and does not quantify postfire vegetation trajectories and decomposition. It also does not include GHG emissions associated with pile burns of forest residue and non-fire natural disturbances, though they are important sources of GHGs.

The methodology also cannot quantify "avoided emissions" from fuel treatments. These result from fires burning less area or burning at lower severities. Fuel treatments may yield a carbon benefit if they contribute to a reduction in the fire severity and resulting tree mortality of a future wildfire on the treatment site.

In the short term, fuel treatments result in carbon emissions, since they intentionally reduce live and dead carbon stocks (Ager et al., 2010). Outcomes for emissions and long-term landscape carbon stocks depend on many factors, including changes in the subsequent frequency, intensity, and rate of spread of fires; the growth response of treated stands in terms of future net sequestration; the amount of carbon emitted from fossil fuel use during the treatment (for transportation and machinery); and the fate of any harvested wood (i.e., furniture, building materials, or other products that can store carbon over long periods). To incorporate these, the method would need to encompass stochastic modeling of wildfire and trajectories of mortality and regrowth over time, as well as the fate of harvested wood. Future improvements to the methods presented in this section may provide a more direct path for evaluating the implications of contemporary fuel management strategies.

GHG Emissions From Pile Burns

This section does not address GHG emissions from pile burning. Forest management activities—regeneration harvests, salvage logging, hazard reduction treatments, restoration, and thinning treatments—and natural disturbances such as mountain pine beetle infestations and windstorm blowdowns create woody debris (often called "slash") and cull piles. This woody debris is commonly collected, by hand or mechanically, into piles for disposal via burning. These piles, which can exceed 50 cubic meters in volume, are allowed to dry for a year or more before they are burned. The combustion process of pile burns and the resultant emissions of GHGs and air pollutants—e.g., fine particulate matter, carbon monoxide, and volatile organic compounds (VOCs)—depend on many factors including the pile geometry, size distribution of woody debris, packing density, pile age, and moisture content (Hardy, 1998; Wright et al., 2009). Users interested in calculating emissions from pile burns are referred to FOFEM (Reinhardt et al., 1997; Lutes, 2019) and the Piled Fuels Biomass and Emissions Calculator (https://www.fs.usda.gov/pnw/tools/piled-fuels-biomass-and-emissions-calculator-tool; Wright, 2015).

Avoided Wildfire Emissions

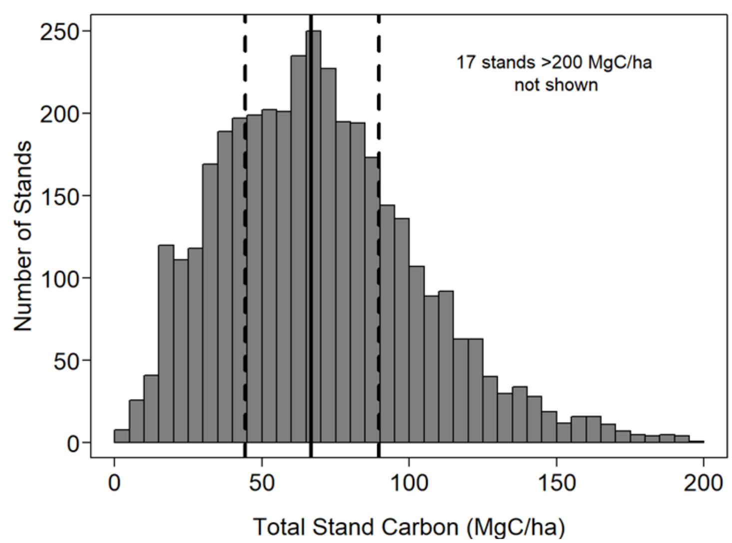
The methods presented in this section offer a means to quantify an important but limited part of avoided wildfire emissions. They are a starting point for land managers seeking to understand the immediate impacts of low-severity prescribed burns and compare them to GHG impacts from higher severity fire events. They are not sufficient as a way to quantify avoided wildfire emissions from forest management activities such as fuel treatments. Such efforts would require more detailed accounting of the carbon costs of the forest management activity (including prescribed fire, diesel and gasoline for transportation and other needs to complete the project), a probabilistic accounting for future fire likelihood and intensity, modeling of regeneration and forest growth over time, spatial information on how the fuel treatment changes probability of burning and intensity on adjacent land, and a long-term model of the fate of burned carbon stocks, regeneration potential, and subsequent disturbance potential.

Uncertainty

FIA Data

The FFE-FVS simulations are based on FIADB TREE table and DDW table data, so uncertainties and errors of these data will be propagated into simulation results. The FIADB DDW table provides estimates of surface fuel loading, litter, duff, and woody material, based on sampling at eight locations for litter and duff and transects for woody material. Perhaps the greatest source of uncertainty in current inventories of standing carbon on the landscape is extrapolation from FIA plots to the rest of the landscape (McGlynn et al., 2019). Surface fuel loading can have tremendous spatial variability (Keane et al., 2012a, 2012b), and the size of a single FIA plot may be inadequate to capture variability in fuel loading across the landscape. Additionally, the diversity in species composition and proportion of consumed biomass can be highly variable. The stochastic nature of fire intensity and severity and the variability of fuels across the landscape compound this uncertainty.

Theoretically, the simulation of multiple FIA plots per forest type captures some of this inherent variability (e.g., see figure 5-8), but when the median simulation estimates are used in reporting, they cannot convey variability in fire effects (see Binning section below). This section addresses this by including 25th and 75th percentiles for each bin as well.



The solid vertical line marks the median value ("best estimate") and the dashed vertical lines mark 25th and 75th percentiles.

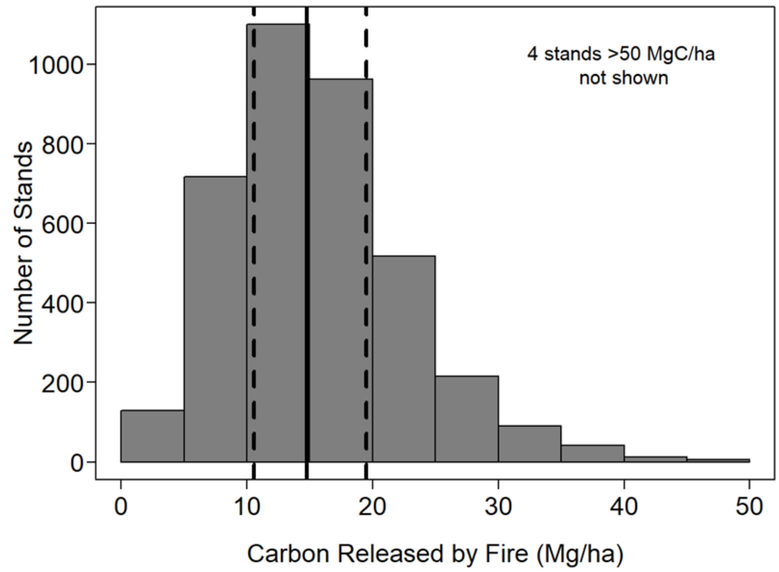
Figure 5-8. Distribution of Total Stand Carbon Prefire in 3,799 Rocky Mountain South Region Ponderosa Pine Forest Stands (Forest Type Group Code = 220)

Fuel Consumption

The FFE-FVS simulations were run using a matrix of fire-related parameters (wind speed, fuel moisture, temperature, and burn patchiness) to approximate the target mortality levels of the fire severity scenarios listed in table 5-12. Consumption of surface fuels, herbs, and shrubs was simulated by FFE-FVS (Rebain, 2010; Reinhardt and Crookston, 2003). Consumption of DDW, litter and duff are largely driven by fuel moisture, although several region-/cover-type-specific algorithms are used for duff.

Binning

The carbon pool and GHG emission estimates are coarsely stratified based on region and forest type, with significant variability among fuel strata. This could result in the binned estimates deviating significantly from true values at any given forest stand. For example, figure 5-9 shows the distribution of simulated total carbon released by moderate-severity wildfire in 3,799 Ponderosa pine forest stands in the Rocky Mountain South region. The total carbon release for half of the stands falls within ±4.5 metric tons carbon per hectare (Mg C/ha) of the best estimate value of 14.8 Mg C/ha. However, one in four stands differs from the best estimate by more than 50 percent (< 7.3 Mg C/ha or > 22.1 Mg C/ha). The span of estimates is likely largely driven by variation in the percent live tree cover and loading of litter, duff, and DDW on different FIA plots within the same region and forest type. Total stand carbon prefire for the same Rocky Mountain South Region Ponderosa pine forest simulations is shown in figure 5-8. Prefire, half of the stands fall within ±22.7 Mg C/ha of the best estimate value of 66.8 Mg C/ha for total stand carbon. Thus, due to the high natural variability of stand structure and carbon pool loading across the sites aggregated by region and forest type in the binning, the median values reported as best estimates may not correspond well with what is on small landholdings.



The solid vertical line marks the median value ("best estimate") and the dashed vertical lines mark 25th and 75th percentiles.

Figure 5-9. Distribution of Total Carbon Released by a Moderate-Severity Wildfire in 3,799 Rocky Mountain South Region Ponderosa Pine Forest Stands (Forest Type Code = 220).

5.2.4 Urban Forest Management

Method for Estimating GHG Flux From Urban Forest Management

- The i-Tree tools currently provide the most comprehensive way to estimate flux from urban forest management. The available tools have varying levels of complexity, thus lending themselves to various user backgrounds.

5.2.4.1 Description of Method

There are three general methods for estimating carbon storage and annual sequestration in urban forests:

- Gathering data on the ground from trees in the field. This method will produce the most accurate estimates, but with increased costs and time spent by the landowner.

- Collecting photointerpretation of tree canopy from aerial imagery. This approach requires a minor time commitment and an ability to discern various geographic features in the imagery. Its accuracy is limited (see table 5-13) due to the conversion from canopy area to carbon data without detailed information on the trees being analyzed.
- Using preexisting and summarized carbon data of specific geographies from an online geospatial database. This approach quickly provides free basic data for the geography of interest but may be out of date or not have a fine enough resolution to be accurate at the local scale.

i-Tree (see box 5-10 for background) is a suite of free software tools designed to assess and value the urban forest resource, understand forest risk, and develop sustainable forest management plans to improve environmental quality and human health. i-Tree tools and resources are referenced for the field data collection method, aerial data collection method, and online spatial database method. Note that these methods may be used in rural areas as well as in urban areas of the United States.

Box 5-10. The i-Tree Suite

i-Tree is a dynamic system of tree benefit estimation science built on a collaborative platform facilitated by a public-private partnership between the Davey Tree Expert Company and the USDA, Forest Service. i-Tree tools calculate not only carbon values, but also many other tree benefits that help inform urban and community forest management. i-Tree serves a growing domestic and global community of users and contributors with online and downloadable tools, user support, and a website with substantial informational and training resources. Collaborators continue to update and expand i-Tree with new tools, science, and reporting options. Because i-Tree is always updating, users are encouraged to visit the i-Tree website at www.itreetools.org for the most up-to-date tools (including the ones listed in this section) and resources including manuals, tutorials, trainings, example projects, and guidance. Some specific i-Tree tools are described in appendix 5-A.6.

The section outlines the use of i-Tree tools to estimate carbon storage and annual sequestration and additional carbon effects, as well as many other environmental services. It offers Level 1, Level 2, and Level 3 approaches that correspond to specific levels of complexity and precision (as described in section 5.1.6).

Table 5-13 compares each of the i-Tree programs. i-Tree programs automatically generate output values of carbon storage and annual sequestration as well as other environmental service values. See section 5-A.1.1 for a description of different approaches to use to collect activity data.

Table 5-13. Data Gathering Methods and Corresponding i-Tree Tools

	Field Data Method	Aerial Data Method	Online Geospatial Database Method
Program	i-Tree MyTree[a] i-Tree Eco[b] i-Tree Design[c]	i-Tree Canopy[d]	i-Tree Landscape[e]
Time needed	Time commitment to take field measurements	Less time to extract aerial data from an existing database	No time, since all data come from existing landcover data

	Field Data Method	Aerial Data Method	Online Geospatial Database Method
Access needed to gather data	Requires access to one or more sample locations across an area	Does not require field measurements, only a computer with internet access	Does not require field measurements, only a computer with internet access
Precision/ accuracy	Increases specificity (relative to the other methods) and accuracy	Returns a more approximate estimate	Returns a more approximate estimate depending on data resolution in the area of interest
Available outputs	Provides a variety of output data including current carbon stock, annual carbon sequestration, and long-term effects	Provides only information on total carbon stored and annual carbon sequestration	Provides only information on total carbon stored and annual carbon sequestration

[a] https://mytree.itreetools.org/

[b] https://www.itreetools.org/tools/i-tree-eco

[c] https://design.itreetools.org/

[d] https://canopy.itreetools.org/

[e] https://landscape.itreetools.org/

i-Tree MyTree is an online program designed for cellphone use that directs users to enter a location and take simple field measurements of tree species, condition, diameter or circumference, and sun exposure to obtain carbon storage and annual sequestration, altered building energy use, and several other environmental service values. Output values are provided in a nutrition label format that can be used in Level 2 calculations. More intensive and precise field data collection methods, using i-Tree Eco, are outlined under Level 3.

i-Tree Design is an online tool for estimating individual tree benefits of carbon dioxide, air pollution, stormwater impacts and energy savings. Users plot an existing tree or planting location on a map, select species, enter trunk diameter or circumference, and select the general condition of the tree to obtain the estimated tree benefits. i-Tree Design estimates tree benefits for the current year and up to 99 years in the future. Total benefits to date based on estimated tree age are also provided. Multiple trees and buildings can be modeled.

i-Tree Canopy is an online photointerpretation tool with underlying Google Earth imagery. Using this tool and online directions, one establishes the location of analysis, enters information about that location, and delineates the area of interest (by drawing a polygon around it or providing a shapefile). With the area of analysis established, i-Tree Canopy automatically generates random sample points, which the interpreter uses to assess tree canopy and/or other land cover values. From the point interpretation and other user inputs, i-Tree Canopy calculates the area covered by tree canopy values and uses the location-specific i-Tree data and models to calculate carbon storage and annual sequestration as well as several other environmental service benefits. The user follows the online instructions to complete the analysis and can export report(s). The i-Tree Canopy values can be exported and used for Level 2 calculations. See appendix 5-A.1.1 for instructions on how to use i-Tree Canopy.

i-Tree Landscape is an online interactive geodatabase that hosts summarized values of carbon storage and annual sequestration as well as many other pieces of forest, environmental, and census information. Using Landscape and following its online directions, one begins by identifying the geographic region to analyze. The smallest level of analyzed geography available in Landscape is the census block group level, but larger census and several other types of geographies are available (i.e., census tracts, watersheds, counties, national forests). Carbon estimates of storage and annual sequestration are calculated from tree cover estimates, themselves derived from land cover data ranging from submeter to 30-meter resolution depending on the area of interest. However, the 30-meter resolution estimates of tree cover, which are most common across the United States, tend to underestimate tree cover (Nowak and Greenfield, 2010) and thus tend to underestimate carbon effects. In addition to carbon, i-Tree Landscape provides additional information of interest for the geography selected. Data from the area of interest can be exported in report(s) and can be used for Level 2 calculations.

MyTree, Canopy, and Landscape can all be used to measure carbon effects over time:

- i-Tree MyTree provides carbon estimates forecasted for a 20-year period and can also be used later to remeasure the trees originally surveyed.
- i-Tree Canopy instructions outline a process to recheck established photointerpretation points with newer imagery (and can check past values if imagery is available).
- i-Tree Landscape has values for different points in time to compare.

Level 1 Approach

To get basic carbon values including storage and annual sequestration, the easiest and most accessible options are to use i-Tree, MyTree, or iTree Design for field data collection, i-Tree Canopy for aerial data collection, or i-Tree Landscape for the online geospatial database method.

Level 2 Approach

Level 2 uses other tools, outputs from Level 1 analyses, and the lookup table values included in this chapter to get a fuller accounting of additional carbon effects and track those impacts over time. MyTree, i-Tree Canopy, and i-Tree Landscape outputs can be used with the lookup tables to account for carbon effects beyond simple storage and annual sequestration. In addition, many i-Tree tools generate some of the additional carbon effects as well as many other environmental service values so that additional work may not be needed.

Use the i-Tree Harvest Carbon Calculator (originally known as the PRESTO Wood Calculator) to estimate the amount of carbon stored in HWPs (i-Tree, 2022b) per forest area (100-year average and total remaining after 100 years or total remaining each first 10 decades as metric tons C/ha with the following categories: products, landfills, stored HWP (sum of products and landfills), emissions with energy capture, and emissions without energy capture). Carbon estimates are based on estimated harvest volumes derived from geographic region, stand size, hardwood or softwood wood type proportions, and sawlog and pulpwood proportions within wood types. This tool offers the means to include HWPs in carbon accounting and carbon credits and to explore the carbon impacts of changing the proportions of longer- and shorter-lived wood products for a given forest stand. It is similar to the Level 1 approach described in the HWP section (section 5.2.2), but it:

- Does not allow the user to choose a forest type.
- Does not allow the user to enter harvest volumes or weights directly.
- Does not include fuelwood or bark.
- Does not include percent loss (immediate disposition) at installation of solid wood products (~8 percent).

- Does not offer both exponential and chi square curves for product in use lifespans.
- Does not use the most recent EPA WARM disposition ratios (recycling, landfills, emitted with and without energy capture).
- Does not report emissions in CO_2-eq.
- Does not connect to a substitution benefit calculator.

For estimating emission effects associated with maintaining urban forests, the following steps are suggested:

1. Determine vehicle use related to tree maintenance. Determine the number of miles driven by various vehicle types.
2. Calculate carbon emissions from vehicles. To estimate carbon emissions from vehicles, the latest fuel efficiency information (in miles per gallon) will be needed for each vehicle class. Divide the miles driven by the vehicle class miles per gallon to determine the total gallons of gasoline (or other fuel) used. Multiply total gallons (or other units) used by the emission factor in table 5-14 to estimate carbon emissions from vehicle use (Nowak et al., 2002).
3. Determine maintenance equipment use. Estimate the number of run hours for all fossil-fuel-based maintenance equipment used on trees (e.g., chain saws, chippers, aerial lifts, backhoes, stump grinders). Estimates of run time for various pruning and removal equipment are given in table 5-15.
4. Calculate carbon emissions from maintenance equipment using equation 5-8. Typical load factors and average carbon emissions for equipment are given in table 5-16.
5. Calculate total maintenance carbon emissions by summing carbon emissions from all vehicles and maintenance equipment.

To determine current net annual urban forest effect on carbon, subtract the carbon emissions from tree maintenance from net carbon sequestration from trees, then add net altered carbon emissions from altered building energy use effects.

Equation 5-8: Calculating Carbon Emissions From Maintenance Equipment

$$C = N \times HRS \times HP \times LF \times E$$

Where:

C	=	carbon emissions (g)
N	=	number of units (dimensionless)
HRS	=	hours used
HP	=	average rated horsepower
LF	=	typical load factor (dimensionless), provided in table 5-16
E	=	average carbon emissions per unit of use (g/hp/hour) (U.S. EPA, 1991)

To determine how tree and maintenance effects on carbon change through time, all the photointerpretation points and the field plots or trees inventoried can be remeasured; subtract previous years' results from most recent years' results to estimate changes in carbon stock, then divide by the number of elapsed years to determine net annual carbon effects, including altered building energy use effects. In addition, maintenance activity estimates should be updated when the remeasurement occurs.

Level 3 Approach

The Level 3 approach uses i-Tree Eco, which is based on field data from samples and inventories, in addition to user input. For further carbon accounting beyond the outputs of i-Tree Eco, calculations from Level 2 can be used.

i-Tree Eco is a downloadable desktop application that uses data collected from trees to assess forest structure, health, threats, and ecosystem services and values for a tree population. It calculates tree benefits including total carbon storage and net annual carbon sequestration, as well as additional benefits such as energy savings, pollution removal, and hydrologic benefits. Carbon storage and sequestration are calculated for each individual tree using species-specific allometric equations (Nowak, 2021). In addition to species, inputs of tree size, condition, and crown light exposure must be gathered to produce carbon storage and sequestration values.

i-Tree Eco also calculates building energy use effects, which it converts to carbon emission factors based on State average energy distribution. Energy effects estimates are based on sampling proximity of trees near buildings within various tree size, distance, and direction classes from a building.

5.2.4.2 Activity Data

Depending on the method used and output values desired, additional steps, data inputs, and/or calculations may be needed to help account for carbon effects beyond the basic values of carbon storage and annual sequestration.

Table 5-14. Emission Factors for Common Transportation Fuels

Fuel	Emissions (Pounds CO_2 per Unit Volume)
B20 biodiesel	17.71 per gallon
B10 biodiesel	19.93 per gallon
Diesel fuel (no.1 and no. 2)	22.15 per gallon
E85 ethanol	2.9 per gallon
E10 ethanol	17.41 per gallon
Gasoline	19.36 per gallon
Natural gas	119.90 per 1,000 cubic feet
Propane	5.74 per gallon

Source: U.S. DOE (2007), table 1.D.1.

Table 5-15. Total Hours of Equipment Run Time by dbh Class for Tree Pruning and Removal

	Pruning				Removal					
dbh	2.3 hp Saw	3.7 hp Saw	Bucket Truck[a]	Chipper[b]	2.3 hp Saw	3.7 hp Saw	7.5 hp Saw	Bucket Truck[a]	Chipper[b]	Stump Grinder[b]
1–6	0.05	NA	NA	0.05	0.3	NA	NA	0.2	0.1	0.25
7–12	0.1	NA	0.2	0.1	0.3	0.2	NA	0.4	0.25	0.33
13–18	0.2	NA	0.5	0.2	0.5	0.5	0.1	0.75	0.4	0.5
19–24	0.5	NA	1.0	0.3	1.5	1.0	0.5	2.2	0.75	0.7
25–30	1.0	NA	2.0	0.35	1.8	1.5	0.8	3.0	1.0	1.0

dbh	Pruning				Removal					
	2.3 hp Saw	3.7 hp Saw	Bucket Truck[a]	Chipper[b]	2.3 hp Saw	3.7 hp Saw	7.5 hp Saw	Bucket Truck[a]	Chipper[b]	Stump Grinder[b]
31–36	1.5	0.2	3.0	0.4	2.2	1.8	1.0	5.5	2.0	1.5
36+	1.5	0.2	4.0	0.4	2.2	2.3	1.5	7.5	2.5	2.0

This table is based on ACRT data (D. Wade and P. Dubish, personal communication, 1995, as cited in Nowak et al., 2002). It assumes that crews work efficiently and equipment is not run idle (Nowak et al., 2002).

[a] Mean hp = 43 (U.S. EPA, 1991)

[b] Mean hp = 99 (U.S. EPA, 1991)

Table 5-16. Typical Load Factors, Average Carbon Emissions, and Total Carbon Emissions for Various Maintenance Equipment

Equipment	Typical Load Factor[a]	Average Carbon Emission (g/hp/Hour)[b]	Total Carbon Emission (kg/Hour)[c]
Aerial lift	0.505	147.2	3.2[d]
Backhoe	0.465	147.3	5.3[e]
Chain saw <4 hp	0.500	1,264.4	1.5[f]
Chain saw >4 hp	0.500	847.5	3.2[g]
Chipper/stump grinder	0.370	146.4	5.4[h]

Sources: U.S. EPA, 1991 (load factors); Nowak et al., 2002 (average carbon emissions, total carbon emissions).

[a] Average value from two studies (a conservative load factor of 0.5 from inventory B was used for chain saws over 4 hp due to disparate inventory estimates; inventory average for this chain saw type was 0.71).

[b] Calculated from estimates of carbon monoxide (U.S. EPA, 1991), hydrocarbon crankcase and exhaust (U.S. EPA, 1991), and CO_2 emissions (W. Charmley, personal communication, 1995, as cited in Nowak et al., 2002), adjusted for in-use effects. Total carbon emissions were calculated based on the proportion of carbon of the total atomic weight of the chemical emission. Multiply by 0.0022 to convert to pounds/hp/hour.

[c] Multiply by 2.2 to convert to pounds/hour.

[d] Mean hp = 43 (U.S. EPA, 1991).

[e] Mean hp = 77 (U.S. EPA, 1991).

[f] hp = 2.3

[g] hp = 7.5

[h] Mean hp = 99 (U.S. EPA, 1991).

5.2.4.3 Limitations and Uncertainty

All three Level approaches can provide carbon estimates for urban areas, with differing degrees of uncertainty and level of effort required. All approaches can also be improved with more field data collection in urban areas, and with model and method improvements related to carbon estimation.

Estimates based on urban tree data collection have fewer limitations than estimates based on aerial data collection, but some limitations exist (Nowak et al., 2008). The main advantage of carbon estimation using the tree measurement approach and i-Tree is having accurate estimates of the tree population (e.g., species, size, distribution) with a calculated level of precision. The modeled carbon values are estimates based on forest-derived allometric equations (Nowak, 1994, 2021; Nowak and Crane, 2002; Nowak et al., 2013). The carbon estimates yield a standard error of the estimate based on sampling error, rather than error of estimation.

Estimation error is unknown, and likely larger than the reported sampling error. Estimation error includes the uncertainty of using biomass equations and conversion factors, which may be large, as well as measurement error, which is typically small. The standardized carbon values (e.g., kg C/ha or pounds C/acre of tree cover) fall in line with values for forests (Birdsey and Heath, 1995), but values for cities (places) can be higher, likely due to a larger proportion of large trees in city environments and relatively fast growth rates due to a more open urban forest structure (Nowak and Crane, 2002; Nowak et al., 2013).

There are various means to help improve the carbon storage and sequestration estimates for urban trees. Carbon estimates for open-grown urban trees are adjusted downward based on field measurements of trees in the Chicago area (Nowak, 1994). This adjustment may lead to conservative estimates of carbon. More research is needed on the applicability of forest-derived equations to urban trees. In addition, more urban tree growth data are needed to better understand regional variability of urban tree growth under differing site conditions (e.g., tree competition) for better annual sequestration estimates. Average regional growth estimates are used based on limited measured urban tree growth data standardized to length of growing season and crown competition.

Estimates of maintenance emissions and altered building energy use effects are also rather coarse. Accurate maintenance emission estimates require good estimates of vehicle and maintenance equipment use; then they rely on an average multiplier for emissions from the literature. Energy effects estimates are based on sampling proximity of trees near buildings within various tree size, distance, and direction classes from a building. Energy factors, converted to carbon emission factors based on State average energy distribution (e.g., electricity, oil), are applied to trees in each building location class based on U.S. climate zone and average building types in a State to estimate energy effects (see McPherson and Simpson, 1999). Though these estimates are coarse, with an unknown certainty, they are based on reasonable approaches that provide defensible estimates of effects. Note that emission reductions from altered building energy use effects might also be implicitly included in any emission estimation an entity might perform based on actual energy use data (e.g., meter readings) for the building in question.

Estimates based on aerial tree canopy effects have the same limitations as field data approaches, plus some additional limitations and advantages. The advantages include a simple, quick, and accurate means to assess the amount of canopy cover in an area, with measures that are repeatable through time. The disadvantage is that the application uses a lookup value from a table (e.g., mean value per unit of canopy cover) to estimate carbon effects. Though the tree cover estimate will be accurate with known uncertainty (i.e., standard error), the carbon multipliers may be off depending on the urban forest characteristics. If average multipliers are used, the accuracy of those estimates will decline as the difference increases between the local urban characteristics and the values of the average multipliers. If local field data are not collected, then the discrepancy between the urban forest's characteristics and those of average values is unknown. However, local estimates may be inaccurate depending on the extent to which characteristics of the local urban forest diverge from the average values.

Estimates based on the landscape tree canopy effects have the same limitations as field data and aerial approaches, plus some additional limitations and advantages. This method is the simplest in that it only requires the user to select an area of interest for analysis. When high-resolution (sub-meter pixel) canopy cover data are available, estimates may be more accurate than those produced by the aerial method. However, where only coarse cover data are available, carbon analysis will be less accurate due to imprecise estimations of canopy cover. Additionally, boundary selection is limited by the tool, such that the smallest urban analysis unit is the census block group.

5.3 Chapter 5 References

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Appendix 5-A: Background Information

5-A.1 General Background Information

The following subsections provide descriptions of activity data, including examples for forest management, as well as the types of estimations.

5-A.1.1 Activity Data

Activity data are measurements or estimations of the magnitude of human activity resulting in emissions or removals during a given period. In the land use context, these data generally take the form of the area in which an intervention takes place (e.g., area to be reforested), typically reported in hectares; they may also be volume of timber harvested or other metrics that parameterize the magnitude of calculation outputs.

The activity data needed for quantifying GHG flux for each forest management activity discussed in this chapter are described in sections 5.2.1, 5.2.2, 5.2.3, and 5.2.4. In many cases, activity data may already be available as part of existing forest management plans or land cover maps or surveys. Users can also use GPS devices to establish the perimeter of an area of intervention to quantify its total area.

Typically, remote sensing—i.e., data collection by unmanned aerial vehicles (drones), aircrafts, or satellite platforms—is used to obtain activity data through well-established methods. Remote sensing of carbon stocks of forest lands and land-use change continues to advance with large-scale (regional and continental), coarse resolution methods with various degrees of uncertainty and site-specificity. This application of remote sensing is commonly referred to as indirect measurement.

Most of the conventional methods for calculating standing stocks of ecosystem carbon and changes in carbon stocks are based on field measurements, whether translated into published default values or derived from stand inventories. In recent years, the scientific community has increased its interest in how remote sensing data could offer a cost-effective alternative to other data collection techniques and could cover larger areas and collect data more often. Appendix 5-A.7 further discusses the status and prospects of remote sensing.

For smaller, less complex areas, such as a farm woodlot or forest stand, entities may define the boundaries geographically using a GPS device. Entities could also use available surveyors' reports or other maps and photos, such as aerial imagery. Alternatively, online tools (e.g., Google Earth) provide detailed land imagery that entities may use to draw boundaries of proposed sites to estimate the area of intervention. Instructions for using i-Tree Canopy and Google Earth are provided below. Land cover maps and plans with delineated boundaries are especially useful; they may include temporal information, such as activities planned for decades in the future (e.g., planned harvests).

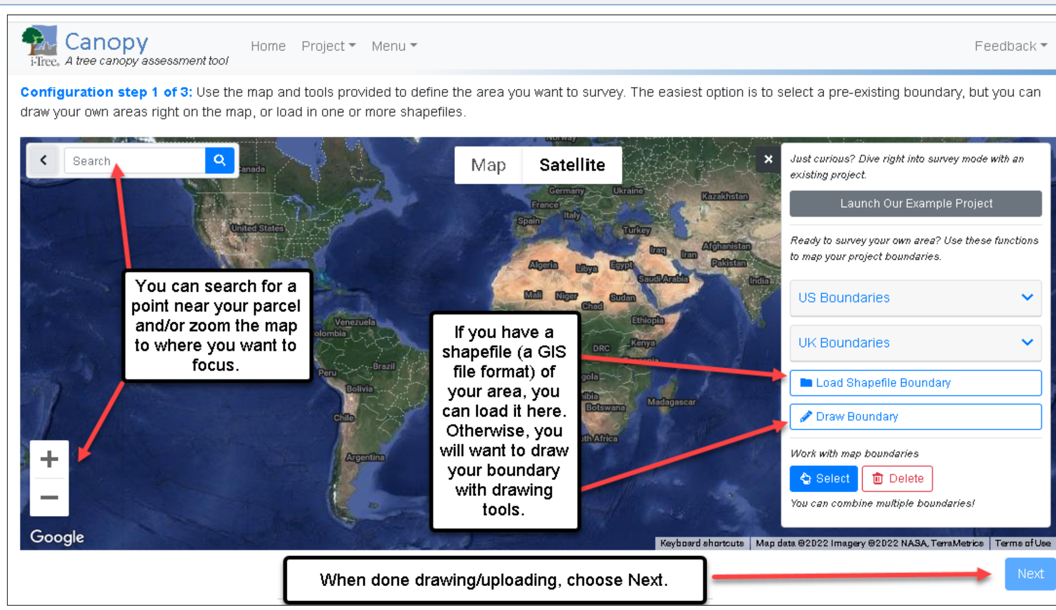
There are a range of options for generating activity data where land cover maps do not exist or where landowners do not clearly understand the total area within each stratum. Other sources of remote sensing data or aerial photography can be useful for any landowner with access to these data but are especially useful for larger land units.

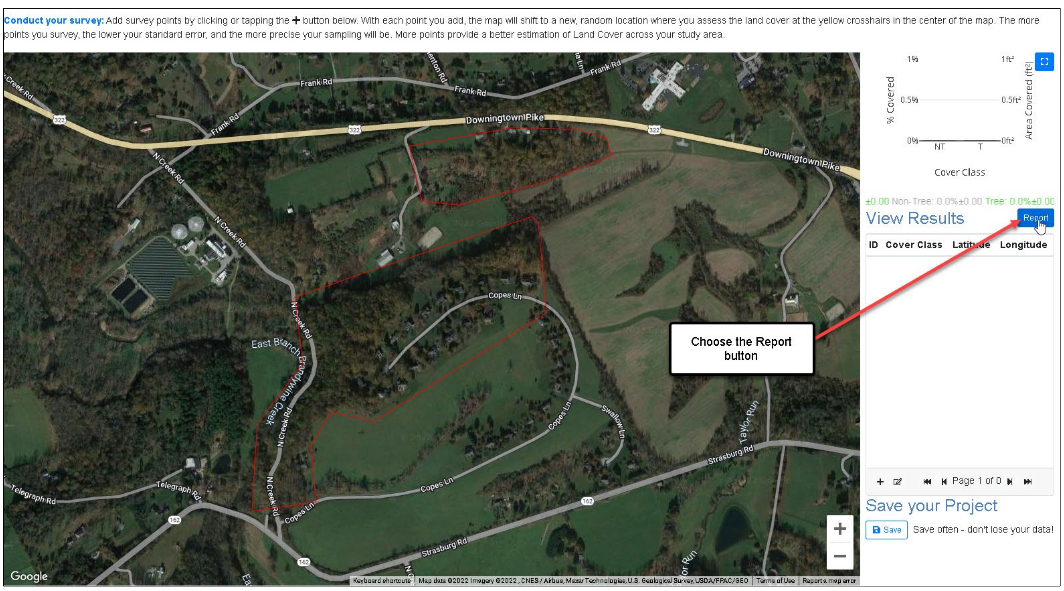
Box 5A-1. Application of GHG Entity Guidelines to Complex Land Ownerships (e.g., Communal Lands, Cooperatives, Some Tribal Lands)

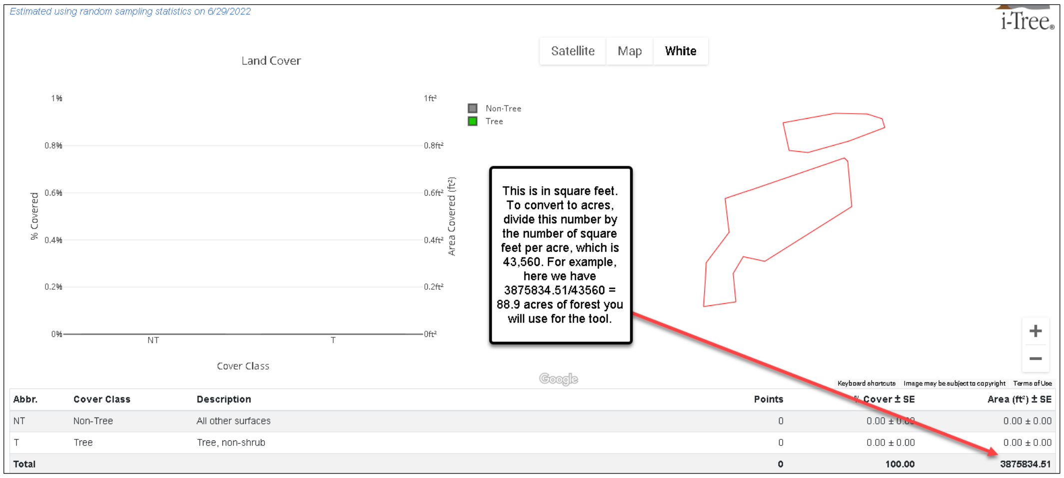
These guidelines work best when applied to land areas where management control is clearly defined and prescribed by a single landowner. It is harder to use them for complex landscapes where individual actors in a communally managed area have more or less freedom to act independently. If actions are agreed upon and prescribed by the communal/cooperative entity in a spatially or temporally explicit plan, the guidelines can be applied as written. Without the ability to precisely identify the spatially explicit activity data necessary—e.g., where individual decisions are more generic and result in a probabilistic management regime rather than being defined by a single management decision or prescription—it may be difficult to follow the guidelines' calculations. Entities may need to use Level 2 or 3 estimation methods to better model the probabilities of various GHG outcomes for the communal entity.

i-Tree Canopy

i-Tree Canopy is a free web tool that is part of the i-Tree suite of tools (i-Tree, 2022d). i-Tree Canopy allows users to estimate land cover and tree cover in areas of interest by interpreting aerial imagery. Entities can use i-Tree Canopy to delineate and estimate the total forest area (activity data) of their forest management activity where data are not currently available, where the property is comprised by a heterogenous mix of forest types, and/or where land cover and stratification is needed. To use i-Tree Canopy, users can follow these basic steps:

Step	Description of Use for i-Tree Canopy
1	Go to the main i-Tree Canopy website (https://canopy.itreetools.org/) and click on the "Get Started" link:
	
2	On the area definition screen, identify the desired area to draw the parcel and visualize it. Use a shapefile (a GIS format file), the address of a nearby point, or zoom in using the "+" button.
	

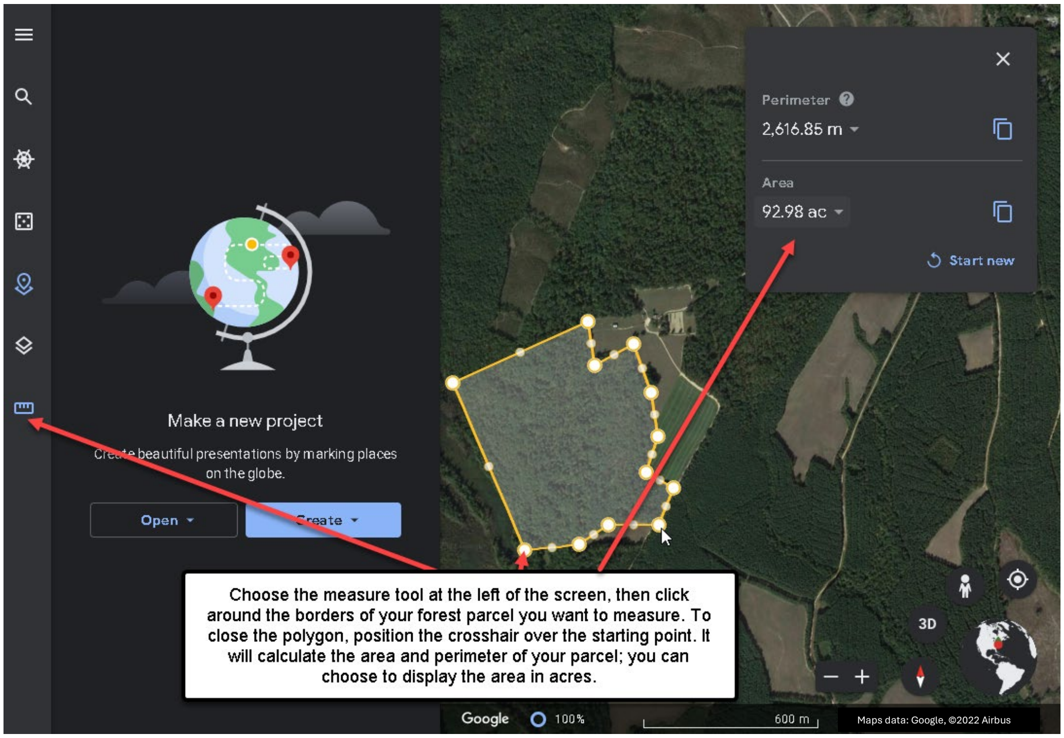
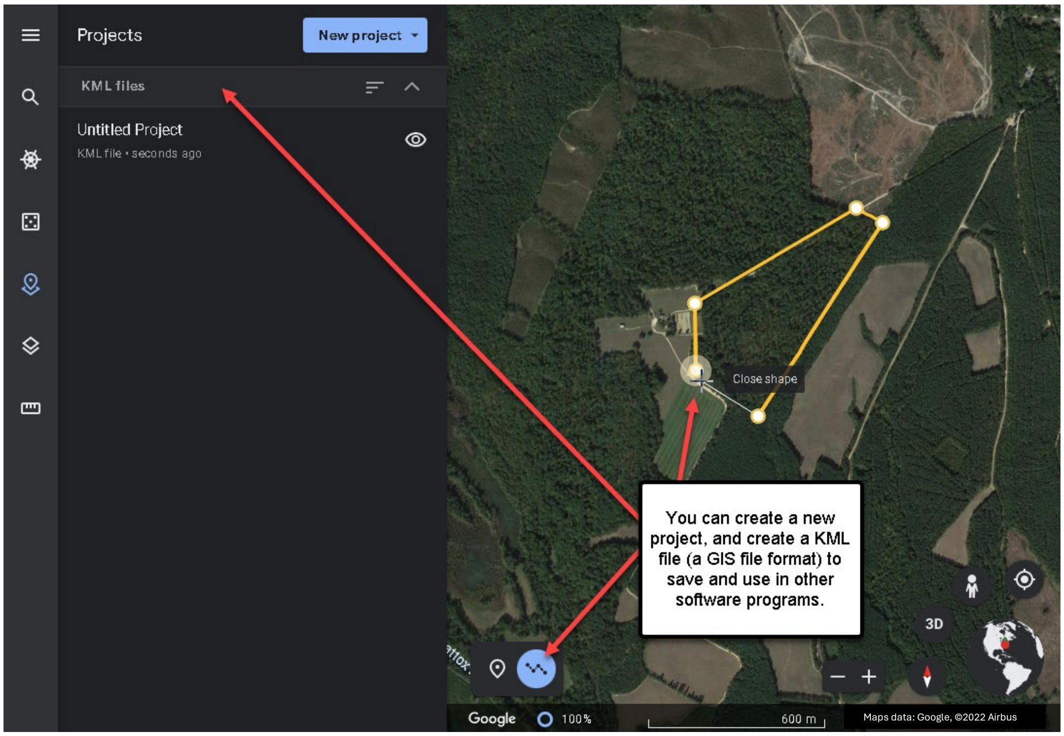
Step	Description of Use for i-Tree Canopy
3	Draw the polygon and choose Next: 
4	Select Next repeatedly until the following screen appears, and choose the “report” button: 

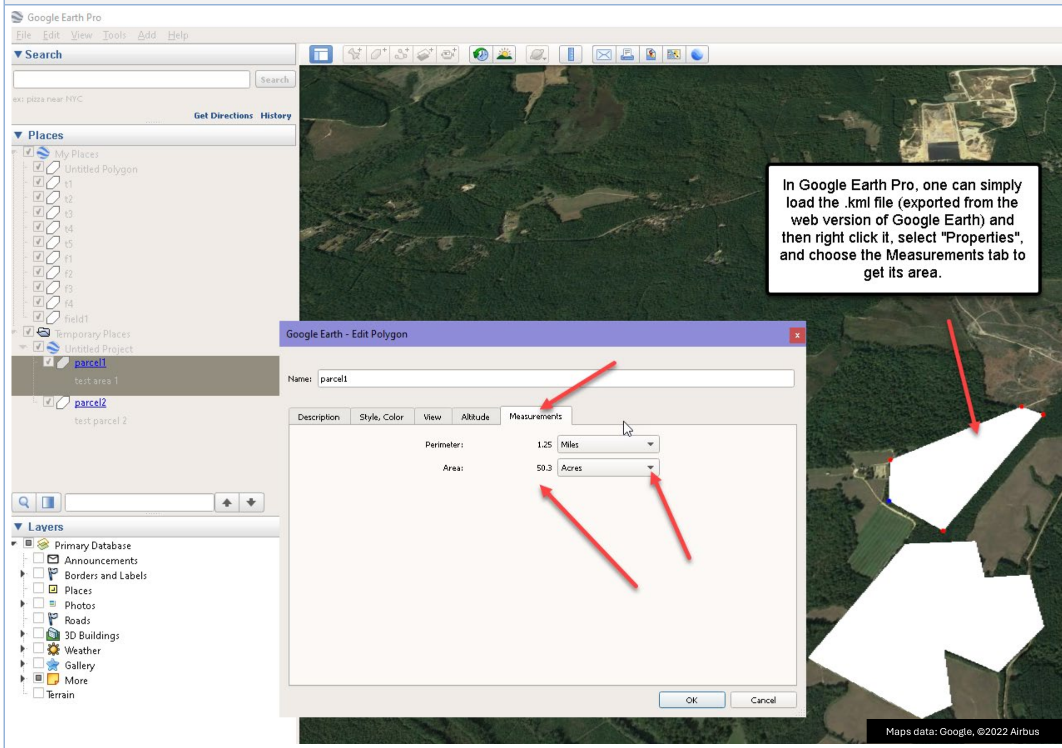
Step	Description of Use for i-Tree Canopy
5	The blank report generated provides the delineated area of the forest parcels. 
6	Save the project to recall the boundaries in the future.

Google Earth

Google Earth is another useful tool for characterizing activity data. The following steps help calculate the area of a forest parcel.

Step	Description of Use for Google Earth
1	Go to earth.google.com and zoom to the area of interest using the search tool ("magnifying glass" button), "+" button, or indicate on the globe: 

Step	Description of Use for Google Earth
2	Use the measurement tool—located on the left side of the screen—to calculate the area. 
3	If needed, create a project and save the parcels. 

Step	Description of Use for Google Earth
3a	For example, the screenshot below shows a project with two parcels that was exported to Google Earth Pro (a free desktop version of Google Earth).
	

5-A.1.2 Stock Change vs. Gain–Loss Approaches for GHG Inventories

There are two standard approaches for GHG inventories of forest ecosystems: stock change and gain–loss. Stock change looks at the change in carbon stocks between two points in time (years), then derives annual flux based on the number of intervening years. The stock change approach is more commonly applied where well-established forest sampling programs exist. The gain–loss approach is more common where those data are lacking; it estimates emissions based on the area of carbon stocks that are converted or degraded, rather than directly measuring changes in carbon stocks over time. With this approach, emissions are estimated as the product of the areas of classes of land-use change (characterized as activity data) and the responses of carbon stocks for those classes (characterized as emission factors). This guidance applies the gain–loss approach for silvicultural Level 1 estimates, as described in more detail in Table 5A-1 and the production approach for HWPs.

Table 5A-1. Activity Data and Emission or Removal Factors Definitions and Examples

	Definition	Examples	Quantification Approach
Activity Data	Measurements or estimations of magnitude of human activity resulting in emissions or removals during a given period; most often, the area of land that is converted from one land use to another is the most important type of activity data (IPCC, 2019)	▪ Area planted ▪ Area of forest managed or treated ▪ Volume of timber extracted ▪ Amount of fertilizers ▪ Area burned	▪ Maps ▪ GPS ▪ Google Maps ▪ Remote sensing
Emission or Removal Factor	The average emission rate of a given GHG relative to units of activity (IPCC, 2019)	▪ Forest carbon stocks ▪ Carbon accumulation/ sequestration rate ▪ Volatilization/oxidation rate of fertilizers	▪ Forest inventory: sampling and allometry ▪ Lookup tables ▪ Simulations/modeling

5-A.2 Silviculture Practices and Improved Forest Management

5-A.2.1 Overview of Silviculture Practices and Improved Forest Management

Silviculture practices may result in emissions in other sectors during management activities, such as the use of fossil fuels (e.g., fuel/oil associated with harvesting equipment). As described in section 5.1.5, this chapter does not include methods to calculate the magnitude of emissions from fossil fuels, with a few exceptions.

This appendix explores the initial, generalized categories of silvicultural practices included under the Level 1 approach and describes how to quantify their impacts on carbon storage, accumulation, and emissions, and offers a brief discussion of other silvicultural and improved forest management practices that could be quantified using a Level 3 approach. (Note that chapter 3 also offers guidance on quantifying GHG flux for agroforestry.)

Timber harvesting results in the removal of biomass from the forest system and a change from standing tree to nonstanding tree carbon pools. The carbon removed from the forest may be converted to forest products such as lumber, paper, pulp, and other products that have longer term but variable decomposition rates—and hence longer term and variable emissions over time. In some cases, short-term sinks of products such as paper and pulp HWPs may be at odds with long-term carbon storage in standing forests. Moreover, wood burned for energy is in effect an emission with substitution effects (i.e., avoiding fossil fuel emissions). See appendix 5-A.3 for a description of these relationships, methods for estimating carbon storage in HWPs, and GHG impacts for potential substitution of wood for more emissions-intensive building products or energy sources. See section 5.2.2 for the chosen estimation methods.

5-A.2.2 Extended Rotation

Extended rotation is when a timber harvest is delayed for 1 or more years, potentially resulting in more carbon accumulating in a forest stand (see figure 5A-1). This is a common practice in the “improved forest management” category of carbon projects that seek to sell offsets via the voluntary or compliance carbon markets. These activities typically occur within even-aged forests by deferring harvest to allow the forest stand to grow undisturbed by human activities, which may result in an increase in standing carbon stocks and those stored in HWPs when a harvest does occur. Although extended rotations may include reductions in harvest intensity, this chapter only addresses modification of time intervals. However, many other modifying metrics could be considered, such as economic criteria (e.g., net present values).

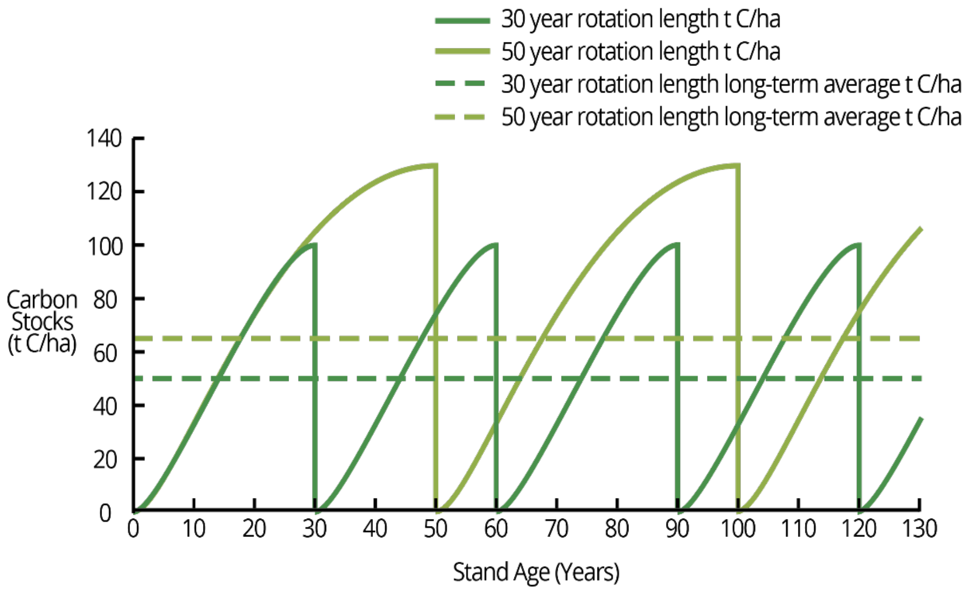


Figure 5A-1. Schematic of Long-Term Average Carbon Storage for Stands Under Different Rotation Lengths

Harvest lengths under conventional silviculture are often based on a careful balancing of biological (i.e., mean annual increment) and economic criteria (i.e., net present value) to maximize yield and investment. When implementing extended rotation to sequester additional carbon, owners may assume some additional costs from stand maintenance and defer profit from timber sales for a few years in favor of sequestering additional carbon and greater future profit, assuming accompanying risks of future disturbance events and highly variable market conditions.

The time for which a rotation is extended beyond its typical length determines the relative benefit of an extended rotation activity: the longer a harvest is deferred, the greater the potential carbon accumulation. However, the relationship between time and carbon accrual is not constant. There may be a point of diminishing returns when considering extended rotation lengths. As figure 5A-2 illustrates, after the initial stages, growth rates and carbon sequestration rates are higher than in the latest stages as the stand ages. Carbon stock continues to increase over time but at a more modest rate. Accordingly, entities should anticipate when peak sequestration/growth will occur to maximize benefits from extending rotation lengths. Further, entities should consider extended rotation activities within the context of overall stand health and resilience: delaying management practices might result in stands becoming overstocked, leading to loss of vigor and resilience. This guidance does not offer explicit analyses of when peak annual accumulation occurs relative to past cumulative accumulation (e.g., stand age 40 in figure 5A-2) among the diversity of forest types included.

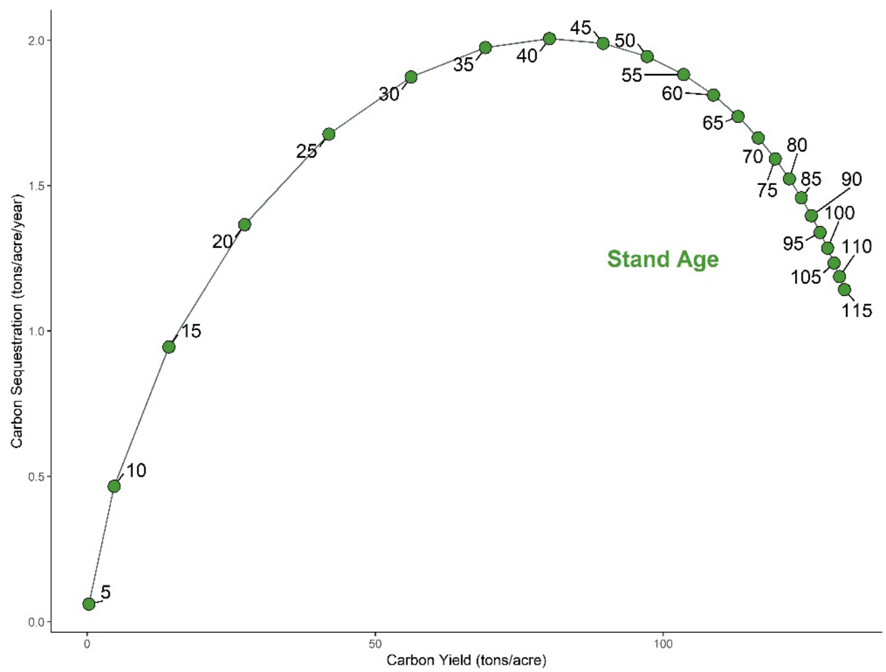


Figure 5A-2. Hypothetical Relationship Between Forest Stand Cumulative Carbon Yield (Tons/Acre) vs. Annual Carbon Sequestration (Tons/Acre/Year) by Stand Age

This guidance offers methods and data for quantifying the benefit of a single extended rotation, as compared to a shorter rotation length, rather than calculating the long-term average carbon benefits over multiple harvests (as shown in figure 5A-2). While the latter would better capture climate benefits as it considers long-term maintenance of the land use, the authors selected the simplified approach in recognition of the timelines relevant to entity owners and the length of time they can realistically commit to management decisions. Rotation cycles are often decades long, and the timelines for accruing long-term benefits over multiple harvests can span generations.

5-A.2.3 Reforestation

Reforestation involves using silvicultural treatments to reestablish forest cover on lands with few or no mature trees. This can be done by preparing the land for natural regeneration and seeding, or by actively planting and protecting seedlings to accelerate the return to forest cover and function. Box 5A-2 discusses definitions of reforestation, but this chapter uses the term "reforestation" for both natural regeneration and human-assisted seeding/planting of trees. The basic methods described in this chapter for quantifying net and annual GHG flux from reforestation do not change based on the extent of human intervention, though the rate at which carbon accumulates can change based on the management intensity of a reforestation project. For example, natural regeneration may only require some basic site preparation, whereas a tree planting project may seek to maximize tree survival through competition control or browse protection which affects the number and growth rate of trees, with important future implications for live tree carbon accumulation and transfers to nonlive tree carbon pools.

Box 5A-2. Reforestation vs. Afforestation

Whether a piece of land was recently a forest or not is important to natural resource sustainability issues and policies that involve tree planting and/or encouraging natural regeneration. Therefore, the terms "reforestation" and "afforestation" are used to distinguish activities based on the condition of land before tree reestablishment.

According to the IPCC (2018), **afforestation** refers to the planting of new forests on lands that historically have not contained forests. **Reforestation** refers to the planting of forests on lands that have previously contained forests but that have been converted to some other use.

These definitions are referenced here because they are commonly used in the literature; however, in terms of carbon accounting for live biomass, there is no practical difference between the two categories. Therefore, this document uses the term "reforestation" for both categories to keep methods approachable for private landowners.

5-A.2.4 Avoided Deforestation

Avoided deforestation is when an intervention prevents an area of forest from being permanently cleared and converted to a nonforest land use (see box 5-1 for a more detailed articulation of the difference between land-use change and land cover change). Where a forest stand is conserved or its harvest intensity is significantly reduced or deferred, its stocks can be maintained, with the stand potentially continuing to sequester carbon in the future.

5-A.2.5 Other Silvicultural Practices/Forest Management Activities

The practices included under Level 1 computations do not reflect the whole breadth of conventional silvicultural treatments (including multi-cohort systems) or the evolving field of climate-smart/adaptive silviculture (ASCC, 2022). Practices such as stand density management (e.g., relative density), species selection, stand structure modification, and site preparation (and other treatments in primarily even-aged stands, as described in table 5A-2) all have impacts on carbon storage and flux. This chapter does not explicitly offer approaches to quantify GHG flux associated with the comingling of all these practices during management operations due to limited data availability and ability to translate those data into user-friendly, Level 1 formats. Future versions of this guidance will seek to expand the set of silvicultural practices covered and potentially take other factors into consideration.

Box 5A-3. Examples of Introductory Resources for Climate-Smart Forest Management

Climate-smart forest management is a set of strategies and management actions intended to support the long-term maintenance of carbon storage benefits from forests and the forest sector. Climate-smart forest management practices bolster forest resilience and provide a broader set of ecosystem services such as water, biodiversity, and soil health (CSF, 2022).

"Forest Management for Carbon Sequestration and Climate Adaptation" (Ontl et al., 2020) offers a menu of adaptation strategies and approaches for forest carbon management based on more than 200 peer-reviewed papers and reports.

"Healthy Forests for Our Future: A Management Guide to Increase Carbon Storage in Northeast Forests" (Marx et al., 2021) introduces and describes 10 forest management practices designed for hardwood forests in New England and New York.

The Northern Institute of Applied Climate Sciences offers several factsheets:

- "Forest Management for Carbon Benefits" (https://www.fs.usda.gov/ccrc/index.php/topics/forest-mgmt-carbon-benefits)
- "Carbon as One of Many Management Objectives" (https://www.fs.usda.gov/ccrc/topics/carbon-one-many-management-objectives)
- "Carbon Considerations in Land Management" (https://www.fs.usda.gov/ccrc/topics/carbon-considerations-land-management)

Those who seek to explore the carbon impacts from silvicultural practices outside those explicitly covered in this guidance, or wish to explore the impacts of more complex, specific, or advanced implementations of the practices that are covered, can consider Level 3 approaches.

Tools and online software platforms are continuing to emerge to support municipal- and entity-scale decision making around climate-smart forestry and policies. A more detailed table of carbon estimation tools and data sources is offered in appendix 5-A.6, and box 5A-4 describes the Land Emissions and Removals Navigator (LEARN) tool, which is designed for municipal-scale GHG inventories and baseline setting.

Box 5A-4. LEARN Tool

The LEARN tool (https://icleiusa.org/LEARN/), developed by the International Council for Local Environmental Initiatives in collaboration with the World Resources Institute's Global Forest Watch and the Woodwell Climate Research Center, was created to help communities estimate their local forests' GHG impacts for forests remaining forests, the effects of reforestation and deforestation, and the effects of selected natural disturbances. LEARN also allows counties and communities to develop a baseline inventory of carbon stocks and stock changes in forests and trees outside forests so they can monitor changes in the GHG impacts of reforestation and deforestation activities, the effects of disturbances occurring within forests remaining forests, and GHG impacts of changes occurring in tree canopies outside forests. The underlying database of removal factors and emission factors was constructed using FIA data and inspired the structure and development of the lookup tables produced for the Level 1 approach employed in this chapter.

Table 5A-2. Common Forest Management Tactics Often Associated With Silvicultural Systems That May Be Modeled Using a Level 3 Approach

Practice	Description	Benefits	Consideration Within This Version of the Guidelines
Stand density management	Controlling the number of trees per unit area in a stand through a variety of techniques, such as underplanting, precommercial thinning, and commercial thinning	Maintains stand at a tree density that provides optimal growing space per tree for best utilization of site resources; allows concentration of site resources on selected trees	▪ Stand density management/thinning are not considered in the Level 1 approach offered in these guidelines, though they are a key area for future refinements. ▪ Under a Level 3 approach, FVS can simulate carbon impacts from thinning practices.

Practice	Description	Benefits	Consideration Within This Version of the Guidelines
Site preparation	Preparing an area of land for forest establishment by removing debris, removing competing vegetation, and/or scarifying soil	Improves survival and initial growth of planted or naturally regenerated seedlings or sprouts; enhances regeneration of desired species; provides conditions favorable for planting of seedlings	Under a Level 3 approach, FVS can simulate impacts from site preparation.
Competing vegetation control	Removing, through chemical or mechanical means, undesirable vegetation that would compete with the desired species being regenerated	Improves survival and growth of desired trees/species	Under a Level 3 approach, FVS can simulate varying mortality rates of desired trees.
Planting	Planting of seedlings by hand or machine to establish a new forest stand; sometimes referred to as "artificial" or "assisted" regeneration	Controls species composition and genetics of newly established stand; controls stocking (density) of trees per unit area for optimal growth/survival	▪ Included under "reforestation." ▪ Enrichment planting (i.e., adding trees to an area with existing forest cover) is not considered. ▪ Agroforestry practices are discussed in chapter 3 (Croplands and Grazing Land Systems). ▪ Planting in urban settings is covered in section 5.2.4 of this chapter.
Natural regeneration	Establishing a new forest stand by allowing/enhancing natural seeding or sprouting	▪ Can result in mix of species ▪ Species that sprout from stumps and roots may rapidly recapture the site ▪ Low-cost relative to planting ▪ May involve less soil disturbance, thereby reducing erosion ▪ Lack of management to control species/density and maximization of growth may result in slower carbon accumulation	Included under "reforestation."
Fertilization	Augmenting site nutrients through the application of nitrogen, phosphorus, or other elements essential to tree growth	Enhances growth of trees; reduces the time for trees to reach merchantable size; eliminates or reduces nutrient deficiencies that would impair forest growth/survival	▪ Not included in Level 1 and 2 options. ▪ Under a Level 3 approach, FVS can simulate fertilizer application on the stand, though fertilizer type and

Practice	Description	Benefits	Consideration Within This Version of the Guidelines
			application loads are limited. ▪ The effects of fertilization are accounted for after growth and mortality have been predicted, so only subsequent cycles are affected.
Selection of rotation length	Choosing the timing of final harvest to control the mix of forest products that can be obtained from the stand (extending a rotation length or deferring a harvest can also serve to sequester additional carbon)	▪ Controls the relative amounts of pulpwood and sawtimber products ▪ Allows landowners to respond to wood product markets by optimizing product mix ▪ Additional years of growth past a baseline rotation length can allow more carbon to be accumulated in the HWPs	This chapter includes Level 1, 2, and 3 options for extended rotation.
Harvesting and utilization	Removal of trees from the forest and cutting and separating logs for forest product markets	▪ Selection of appropriate harvesting systems can provide logs for markets while minimizing damage to residual trees or disturbance of soil. ▪ Choice of harvesting and silvicultural system will impact subsequent regeneration of the stand; systems can be chosen to influence the species composition of the regenerated stand.	This chapter discusses wood harvest, carbon stored in wood products, and climate benefits from substitution of wood products for more emissions-intensive products. The Level 1 approach is described in section 5.2.2.
Fire and fuel load management	Reducing the risk of loss to wildfire by controlling the quantity of fuels in a forest stand using controlled fire or mechanical treatments	Reduces the damage caused by severe wildfires by eliminating excessively high fuel loads; may influence the species composition of the understory	Section 5.2.2 includes Level 1 and 3 options for prescribed burning.
Reducing risk of emissions from pests and disease	Recovering value of timber after damaging events and/or preventing further damage by interrupting spread/intensity of pests/diseases. Reducing risks from emissions from pests and diseases requires managing stand density to keep density below the species-dependent	Salvage harvests recover value in damaged timber by removing it before it is unusable; sanitation harvests prevent spread of pests/diseases.	▪ Level 1 guidance in these guidelines does not include this practice. ▪ Under a Level 3 approach, FVS can simulate carbon impacts from thinning practices.

Practice	Description	Benefits	Consideration Within This Version of the Guidelines
	thresholds defined by research.		
Short-rotation woody crops	Producing merchantable trees in very short periods through intensive management (e.g., genetics, herbicide, fertilization)	Reduces the time for trees to reach merchantable size; often results in HWP with shorter life cycles but with important substitution effects such as bioenergy	This version of the guidelines does not include this practice.

The descriptions in the table above assume forests begin growing at one point in time so that all trees are nearly in the same age cohort. This assumption greatly simplifies the complex array of silvicultural systems that owners consider when they wish to increase the biodiversity, resiliency, or structural diversity of their forest by eliminating those generally applied to uneven-aged systems (e.g., seed tree, shelterwood, or irregular shelterwood). This simplification is an important constraint on the utility of this guidance for many family forest and small corporate landowners.

Silvicultural practices traditionally aim to enhance the provisioning of merchantable timber, which inherently seeks to maximize biomass accumulation in the stems/boles of the trees. However, climate-smart forest management practices instead seek to enhance whole-stand biomass across a variety of carbon pools, species combinations, and stand structures, which can serve as a buffer to global impacts, such as climate change and invasive insects and diseases. These practices also focus on non-timber components, such as limiting soil disturbance or maximizing biodiversity to increase the resilience of forests to future global change.

Many managed forests are subject to various climate-change-related stressors brought on by interacting patterns of rising temperatures, drought, and native or invasive pests and diseases (Koch and Ellenwood, 2020; Koch and Potter, 2020). Forest owners seeking to maximize carbon should do so with an eye toward sustaining long-term resilience on their lands. This means considering climate vulnerability; undertaking long-term maintenance of ecosystem services beyond carbon; and seeking out practices that can support ecosystem adaptation to conditions that may be warmer, drier, fire prone, or subject to extreme weather events.

The carbon stored in forests is always at risk of emission due to episodic disturbances (e.g., wildfires) or chronic health decline (e.g., single-species stands suffering from insect attack)—a risk that varies across space and time. In other words, inadvertent “reversals” of low-carbon-management actions can also lead to emissions. In many cases, there may be synergies among these considerations that help maintain current forest carbon stocks, reduce emission risks to the atmosphere, and/or enhance carbon retention in the long term.

Entity owners should consider these trade-offs when evaluating silvicultural options and consult with professional foresters when considering harvests or other silvicultural practices, no matter what their management objectives are. Fundamentally, entity owners seeking to adopt silvicultural practices are advised to consider those that support the long-term health of the forest (e.g., soil health and tree regeneration/recruitment dynamics) and the other objectives important to individual landowners (e.g., wildlife habitat, aesthetics), rather than focusing solely on live tree carbon accumulation.

5-A.2.6 Background for Lookup Tables

The values for carbon stocks and change in the Excel workbook lookup tables represent the average values of observations and measurements collected from plots that fit the variables used in the analysis: region, forest type group, stand origin, and stand age. In some cases, these values showed the forests are a source of emissions, rather than sequestration. This may be due to a number of reasons:

- The value is a true reflection of carbon dynamics playing out across many Western landscapes. As shown in national analyses by Domke et al. (2020) and Domke and Murray (2021), forests in several intermountain States—most notably Colorado and Montana—have become carbon sources, not sinks, due to the severity and frequency of disturbances in recent years. This trend is also reflected in other summaries of FIA data, such as Hoover and Smith (2021).
- Too few plots matched the particular combination of variables in question and estimates for the plots varied considerably. In these cases, the sampling error is very high and should not be considered an accurate representation of carbon stocks or carbon stock change.
- The selection of variables used to group the FIA plots upon which the Level 1 analysis of carbon was performed does not fully account for the diversity of management practices that may have been adopted at or near the individual plots. This lack of accounting is due to the limitations associated with the approach for applying FIA data instead of model carbon outcomes.

Box 5A-5 below also provides more context on how carbon values are rendered in the FIADB and outlines planned developments in the database outputs.

Box 5A-5. Models and Data for Carbon Pool Estimation: Existing Structures and Future Trajectory for the FIADB

The FIA program provides estimates of DDW, litter, and soil carbon in the FIADB for every condition on national forest inventory plots that meet the definition of forest land (USDA Forest Service, 2022f). These estimates are obtained from models developed using geographic area, forest type, and plot-level attributes (e.g., live tree carbon density, stand age) or auxiliary information (e.g., Digital General Soil Map of the United States). The FIA program has also been measuring DDW, litter, and soil attributes on plots with at least one forest land condition since 2001 (USDA Forest Service, 2022f). These data are collected on a subset of base intensity FIA plots. While the protocols used to sample and measure DDW, litter, and soil attributes have changed over the last 20 years, it is possible to use these observations to estimate status (e.g., carbon stocks) and trends (e.g., carbon stock changes) (Woodall et al., 2021).

The DDW, litter, and soil attributes measured on FIA plots over the last few decades have also been used to develop new methods and models to characterize carbon stocks on plots with these attributes, as well as forested plots without direct measurements of DDW, litter, or soil attributes (Domke et al., 2016, 2017; Smith et al., 2021). These contemporary models not only rely on observations of DDW, litter, and soil attributes from the FIA program, but also include climate variables, physiographic factors, and vegetation type. These models have been used in national GHG reporting (U.S. EPA, 2022) and several State-level reporting activities (Christensen et al., 2021), and will soon replace the models currently used in the FIADB.

5-A.3 Harvested Wood Products

5-A.3.1 HWP Carbon Storage and Emission Inventory

IPCC (2019) provides guidelines for nations to estimate carbon stored and emitted from the HWP pool using one of three tiers (Tiers 1–3) and one of three approaches (production, stock-change, and atmospheric flow), but always using the production approach as part of the reporting. The production approach considers all wood produced by a given entity, regardless of where it is used or disposed of. Thus, while carbon stored in and emitted from HWPs exported outside a reporting country is included, the same from imported HWPs is excluded. Ensuring all nations provide estimates with this production approach means that all HWPs should be comprehensively captured when they are attributed to their country of origin. This helps avoid very challenging accounting, considering that many wood products are exported and serve as inputs to additional processing. Several teams have modeled the IPCC production approach at smaller scales than the entire United States (e.g., Anderson et al., 2013; Loeffler et al., 2019) and some have combined ecosystem and HWP estimates in the same report (e.g., Christensen et al., 2021). To report all emissions, Ganguly et al. (2020) adopted the production approach to account for production emissions and wood products carbon storage in a Washington State study. This appendix guides individual landowners through carbon storage and emission estimation starting with the production approach, where the entity is claiming storage and emissions associated with just HWPs grown from their land.

The HWPs include fuelwood (contained carbon is assumed to be emitted as CO_2 during the year of harvest), as well as logs that are processed into a wide range of primary and secondary wood products. Processing logs into wood products creates "fuel and other" coproducts and a range of feedstock (e.g., pulp chips, sawdust, wood shavings) used to create other HWPs (e.g., paper, paperboard, particleboard, hardboard). Mills burn some of the "fuel and other" material, which is biogenic carbon, to offset some of the electrical and thermal energy required to saw, sort, and dry the primary wood products. Many of the products are used in construction or furniture and have long lives in the products-in-use HWP subpool before they are disposed of. Some products, like paper and packaging, tend to have shorter lives.

There is some continuing debate on how to handle wood bark. Ganguly et al. (2020) assume that most of the bark transported to sawmills, plywood mills, or pulp mills with logs (accounting for 6.06 percent of the logs' volume) is used at the sawmills as hog fuel. This assumption is common among researchers, who consider bark from sawlogs, veneer logs, pulpwood, and fuelwood to be emitted through burning in the year of harvest. The bark, branches, and tops that stay on the forest floor are either burned (through pile or prescribed burning) or assumed to decay over time (Lippke et al., 2011; Ganguly et al., 2018). This assumption means that most of the bark never enters the products-in-use pool, making how and where to count it mainly an issue of holistic emissions accounting. Other authors point to landscaping woodchips as examples of short-lived wood products derived from tree bark (Brandt et al., 2006; Simmons et al., 2016, 2019). As stated in section 5.2.2, because this chapter looks at the overall carbon removals and emissions from forestry activities, carbon transitions from bark harvested in combination with HWP feedstock reported with underbark units should be reflected as changes in either ecosystem and/or HWP pools. Smith et al. (2006) provided ratios to estimate wood bark volume relative to sawlogs and pulpwood (not fuelwood). However, they did not include any bark products in their primary product allocations, and thus bark products are omitted from any estimates of fractions remaining over time.

The 2019 Refinement to the 2006 IPCC Guidelines (IPCC, 2019) does not provide explicit guidance on how to handle tree bark carbon content in accounting for GHG flux. Although bark is attached to logs brought from the forest to mills, it is not considered part of the underbark feedstock of wood removals or roundwood according to IPCC definitions. Some of this confusion stems from the fact that bark is not part of the typical log volume measures of cubic meters, CCF, or MBF, where scaling log inputs are directly linked to expected final nominal product outputs. Research shows that most tree bark is removed from trees by debarking at mills and burned with energy capture, along with some of the sawdust, trimmings, planer shavings, and other wood removals that constitute fuel and other coproducts (shown in Smith et al., 2006, table 6). In reality, bark and these processing coproducts are often mixed together, depending on their economic values, to optimize boiler operations for onsite energy at the mills. For this chapter, the authors assumed that estimated bark carbon was burned with energy capture in the year it was produced, that bark ratios from Smith et al. (2006) indicate the carbon content, and "mill residue" was used for heating value for this fuel. (Future work may replace this assumption if better information becomes available.) The bark emissions from roundwood (but not logging residues) are used in the LCA potential substitution calculator.

Although it is not included in the harvest carbon calculator results summary, the authors assumed that the estimated bark carbon used in the potential substitution calculator was burned in the year it was cut applying the Smith et al. (2006) table D7 coefficient "a" factors for energy capture. These bark emissions are used in the LCA potential substitution calculator described in section 5.2.2.1. A full discussion of wood bark accounting and assumptions is included in appendix 5-B.2.2. Thoughts for including bark utilization in forest sector carbon accounting are also discussed in more detail in Lucey et al. (in review).

HWP models have traditionally used exponential decay functions to simulate discard of HWPs from use over time and decomposition of discarded HWPs in SWDS. These exponential decay models rely on estimated half-lives—the number of years it takes for half of the amount of material in-use to be discarded. Some researchers (e.g., Bates et al., 2017) have shown that alternative gamma decay functions may better represent the rates at which products in use transition to disposal. The text below describes both of these decay functions.

Box 5A-6. Decay Functions

Decay functions are used to determine the duration of each primary product end use, as well as the actual wood decay rates in landfills. The result of combining these decay rates provides some valuable insight. The disposition distributions cited in this document (U.S. EPA, 2020b) show that 67 percent of solid wood products end up in landfills, where 88 percent remains stored in anoxic environments. Multiplying these percentages shows that 59 percent of the carbon in solid wood products remains permanently stored in landfills. Similarly, 26 percent of paper is disposed of in landfills where 44 percent remains permanently stored, meaning 11 percent of the carbon remains permanently stored.

These are percentages of the primary products that were made, not percentages of the trees that were cut. The modeling recommended here uses regional primary product ratios to account for this additional factor, which determines the percent of delivered logs converted into primary HWPs. The percent of all trees remaining permanently stored is smaller yet, because not all cut trees or all parts of removed trees are transported out of the ecosystem to processing facilities or as fuelwood.

Most U.S. carbon modeling has estimated the end-of-life phase using proportions of disposal going to recycling, landfills, and burning with and without energy capture. Most of the solid wood carbon that goes from products in use to the SWDS subpool (i.e., landfills) remains stored due to the anoxic environment that prevents decay (less so for paper products). Some of the landfilled carbon is emitted as CO_2 and some as CH_4. IPCC recommends that compilers of the AFOLU sector report CO_2 emissions, but the CH_4 emissions are included in a different waste sector. U.S. EPA's WARM notes that almost all U.S. solid and engineered wood waste ends up in dry solid waste landfills or is burned with or without energy recovery. Based on the U.S. EPA WARM report, of all the carbon in wood that ends up in solid waste landfills, only 1 percent of the initial carbon is assumed to be emitted as CH_4 as lifetime landfill emissions. This CH_4 emission, though small, is not captured for energy and gets emitted into the atmosphere (U.S. EPA, 2020b). Appendix 5-B.2 addresses the complexities of the IPCC production approach and provides an example of how to use the Level 1 harvest carbon calculator to estimate HWP stocks and emissions.

The production approach to accounting for HWP carbon storage and emissions is different than an LCA approach. The LCA approach focuses on the fossil CO_2 emissions generated through a product's life cycle and evaluates the environmental impacts from these emissions. More detail on the LCA approach is provided in appendix 5-A.3.2.

5-A.3.2 LCA Overview

The LCA approach is used to estimate the total environmental impacts from producing a product or service. Life cycle analysts first produce a holistic inventory of a product's GHG emissions from raw material extraction to product manufacturing, in some cases extending to products' use and end-of-life processing, also including transportation between stages (illustrated in figure 5A-3). Then, using internationally accepted impact assessment methods, life cycle analysts can quantify the environmental impacts (e.g., global warming impact expressed as CO_2-eq) from input attributes like resources and energy use.

Full LCA with a cradle-to-grave boundary system is beyond the scope of this chapter. The cradle-to-gate LCA adopted instead (see figure 5A-3) quantifies GHG emissions from HWP life stages including harvest, material transportation, and product manufacturing, but omits use and end-of-life stages, and therefore does not calculate total global warming impacts. This chapter does provide insight into HWPs' potential GHG impacts, including potential GHG reduction benefits of substitution wood products for functionally equivalent nonwood products, based on LCA-quantified GHG emissions.

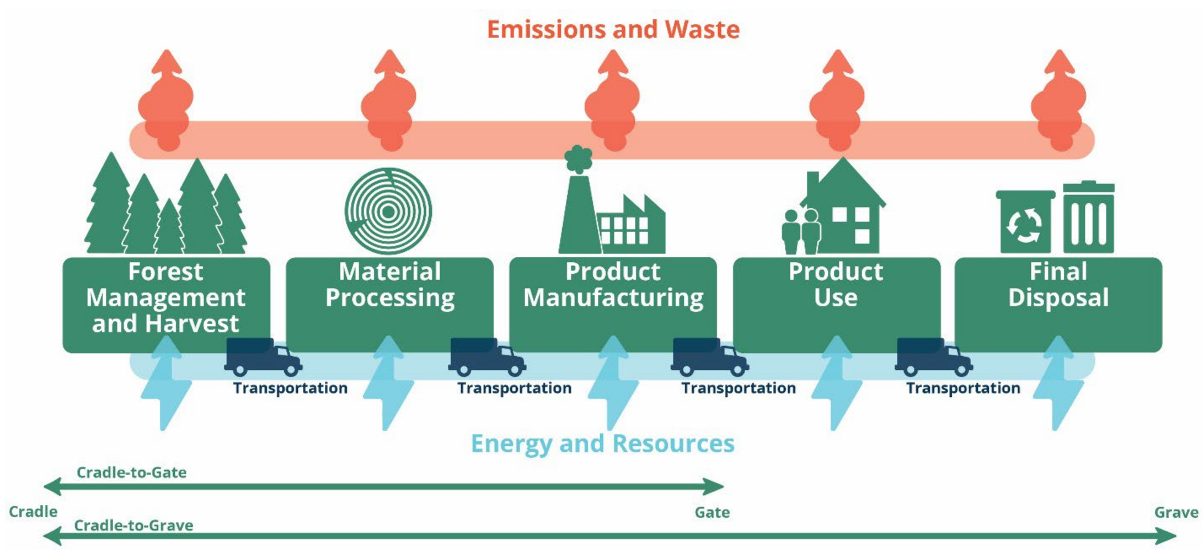


Figure 5A-3. Generic Presentation of Life Cycle Stages of HWPs in LCA Studies

The estimated life cycle GHG emissions of HWPs in this chapter are based on attributional LCA studies by the USDA Forest Products Laboratory and the Consortium for Research on Renewable Industrial Materials. But the estimated GHG reduction benefits associated with substitution of wood for functionally equivalent nonwood products is based on consequential LCA, in which it is assumed that all produced HWPs are used to replace their functionally equivalent nonwood products. The attributional LCA information used in the chapter covers life cycle stages up to the product manufacturing—i.e., cradle-to-gate (or production gate)—system boundary, which includes quantification of GHG emissions from forest management and harvesting operations, transportation of raw wood materials (e.g., logs), and HWP manufacturing activities. The LCA information used in this chapter covers softwood lumber, hardwood lumber, softwood plywood, oriented strandboard, nonstructural panels, and other industrial products, along with energy products from fuelwood. All inputs and outputs are scaled to produce 1 metric ton of each primary product. The flow of biogenic carbon in the LCAs for HWPs is treated separately from fossil CO_2 emissions, as per the requirements of the ISO 21930:2017 standard.

The GHG emissions and estimated substitution factors developed as part of the LCA analysis for this guidance were based on LCA studies performed on different HWPs. All the LCA studies used the TRACI 2.1 impact assessment method, which incorporates GWP values from the IPCC Fourth Assessment Report (i.e., CO_2 = 1, CH_4 = 25, N_2O = 298) (IPCC, 2007, table TS.2). As such, the GWP values used to develop the substitution factor values deviate from IPCC (2013) GWP values presented in chapter 2.

Box 5A-7. LCA-Reported GHG Emissions: 100-Year Approach

After being released, GHGs absorb the heat from solar radiation and cause a warming effect, which can be assessed over the period for which these gases stay in the atmosphere.

An increased abundance of GHGs in the atmosphere, primarily due to the release of fossil-based CO_2 emissions, is increasing global temperature. The net warming impact of GHG emissions is presented as the GWP number in the LCA methods.

A 100-year approach considers the warming impacts of different GHGs up to 100 years once they are released from HWP life stages. Though researchers have compared other approaches with short (20-year) and long (500-year) timeframes, the 100-year approach has been most popular as a balanced choice that allows policymakers to compare different emissions-saving opportunities.

5-A.3.3 Substitution Benefits of HWP

Use of wood instead of functionally equivalent nonwood material avoids significant fossil CO_2 emissions that would have occurred if nonwood products were used (figure 5A-4): for example, wood fuel substituting for fossil-based heat and electricity or transportation fuels, or engineered wood products substituting for concrete and steel structural materials. Because of such avoided emission benefits, HWPs are considered an important part of climate change mitigation strategies and their substitution impacts are widely reported around the world (Leskinen et al., 2018; Hurmekoski et al., 2021; Soimakallio et al., 2022). The LCA-based estimates of GHG emissions of wood products and their functionally equivalent nonwood products can be used to derive the substitution factors are also known as displacement factors. These factors can be further used to quantify total potential benefits from HWP substitutions from forest harvests. This chapter makes no comment about incremental change in HWPs but provides the accompanying Excel workbook that estimates the maximum potential substitution. This quantification of the potential substitution benefits helps inform landowners and policymakers developing forest management and harvesting strategies aimed at realizing higher total GHG reduction benefits.

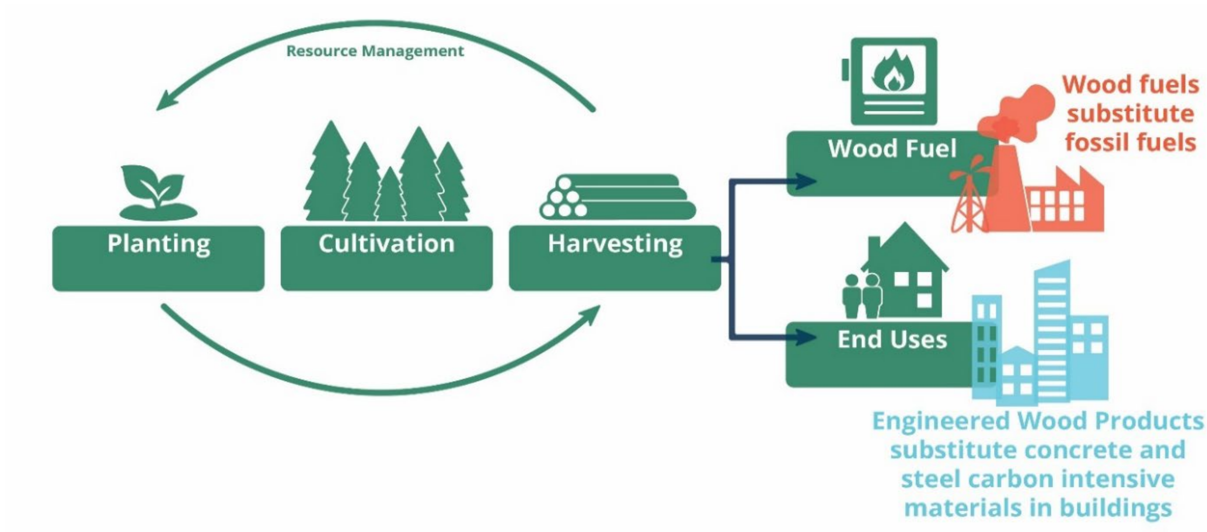


Figure 5A-4. HWP Substitution to Reduce GHG Emissions

5-A.4 Wildfire and Prescribed Fire

Most of the fuel carbon volatilized by combustion is released as CO_2. On average, non-CO_2 products such as CO, CH_4, VOCs, and carbonaceous particles constitute less than 5 percent of volatilized carbon (Urbanski et al., 2022). In addition to CO_2, fires produce the GHGs CH_4 and N_2O (Urbanski, 2014).

Box 5A-8. Impact of Non-GHG Emissions and Particles Produced by Fire

The particles produced by fires also have direct and indirect impacts on climate, but these climate effects are not fully understood and are highly uncertain (Fuzzi et al., 2015). Unlike CO_2, CH_4, and N_2O, these particles reside in the atmosphere for a few days to a couple of weeks before they are removed by cloud droplets or precipitation or transported to the surface by atmospheric turbulence. Non-GHG emissions can have a significant impact on air quality. Carbonaceous particles include fine particulate matter, the main component of wildfire smoke that affects public health (Aguilera et al., 2021; McCaffrey et al., 2022). VOCs and nitrogen oxides (e.g., NO and NO_2), which are also produced by fires, can undergo atmospheric chemical reactions to produce ozone (O_3), another atmospheric pollutant with significant health impacts (Alvarado et al., 2022; McCaffrey et al., 2022).

Indirect emissions result from fire-induced vegetation mortality, which alters subsequent carbon dynamics. In the short term, reduced live vegetation reduces photosynthetic carbon uptake while the decomposition of dead vegetation increases ecosystem release of CO_2 (Marañón-Jiménez et al., 2011). As trees killed by fire continue to decompose, biomass can be converted to atmospheric carbon for many decades postfire (Kashian et al., 2006). However, vegetation recovery and regrowth can compensate for postfire decomposition in as little as 5 to 6 years in some ecosystems, such as high-severity fires in Michigan jack pine and low-severity fires in the Eastern Cascades of Oregon (Rothstein et al., 2004; Meigs et al., 2009). In other ecosystems, carbon emissions might continue to outpace postfire carbon uptake for decades. Prefire carbon stocks may never completely recover in some cases, for example if repeated large, high-severity fires or changes in climate inhibit regeneration (Davis et al., 2019) and drive conversion of coniferous forests to shrub fields (Loehman et al., 2014). Carbon dynamics are affected in the long term through the postfire trajectory of vegetation growth, structure, and species composition, as well as by the timing and severity of future disturbances such as fires, insects, and disease.

Section 5.2.3 reports immediate changes in carbon pools and instantaneous GHG emissions resulting from wildland fire. The methods described in this section offer a starting point for land managers seeking to understand the immediate impacts of low-severity prescribed burns and compare them to GHG impacts from higher severity fire events. The methods presented are limited, though potentially informative in the context of a more indepth analysis of avoided wildfire emissions. Indirect carbon emissions are not addressed. However, the approach used to estimate the immediate fire effects could be extended to provide long-term, postfire trajectories of carbon pools and GHG fluxes.

5-A.5 Urban Forest Management

5-A.5.1 Overview of Urban Forest Management

Like all forests, urban forests—and urban forest management activities—both generate emissions and remove carbon from the atmosphere. Urban forests have some distinctions from peri-urban or rural forests: they are often arranged differently due to the higher density of buildings and other infrastructure, and they are managed for different objectives. Rather than timber production, urban forests are managed for a wide array of functions, including shade, privacy, stormwater runoff mitigation, recreation, noise reduction, urban wildlife habitat, and aesthetic and cultural value. Therefore, the composition of tree species, arrangement of trees, and distribution of trees in urban spaces is highly variable and distinct.

In addition to storing carbon in trees, the urban forest has secondary impacts on atmospheric carbon by affecting carbon emissions from urban and community areas. Tree care and maintenance practices often release carbon back to the atmosphere via fossil fuel emissions from maintenance equipment (e.g., chain saws, trucks, chippers). Thus, some of the carbon gains from tree growth are offset by carbon emissions via fossil fuels used in maintenance (Nowak et al., 2002).

Because they are located where human population is denser and interactions with buildings and other infrastructure are greater, urban trees and forests often have a more direct impact on the built environment. Trees strategically located around buildings can reduce building energy use (e.g., Heisler, 1986) and consequently reduce carbon emissions from fossil-fuel-burning power plants. These energy effects are caused primarily by tree transpiration (lowering of air temperatures), blocking of winds, and shading of buildings and other surfaces. Trees typically lower building energy use in summer but can either lower or increase building energy use in the winter depending upon their location relative to a building.

Emissions from energy-related source categories (e.g., transportation, fuel use, heating fuel use) are typically considered outside the sectoral boundaries of GHG accounting within the AFOLU sector, as described in section 5.1.5. This chapter includes them because of the readily available methods built into the i-Tree suite of tools to account for emissions from urban forest management activities. However, consider sector boundaries and be deliberate in including or excluding non-land use sector carbon flux when establishing accounting and monitoring systems.

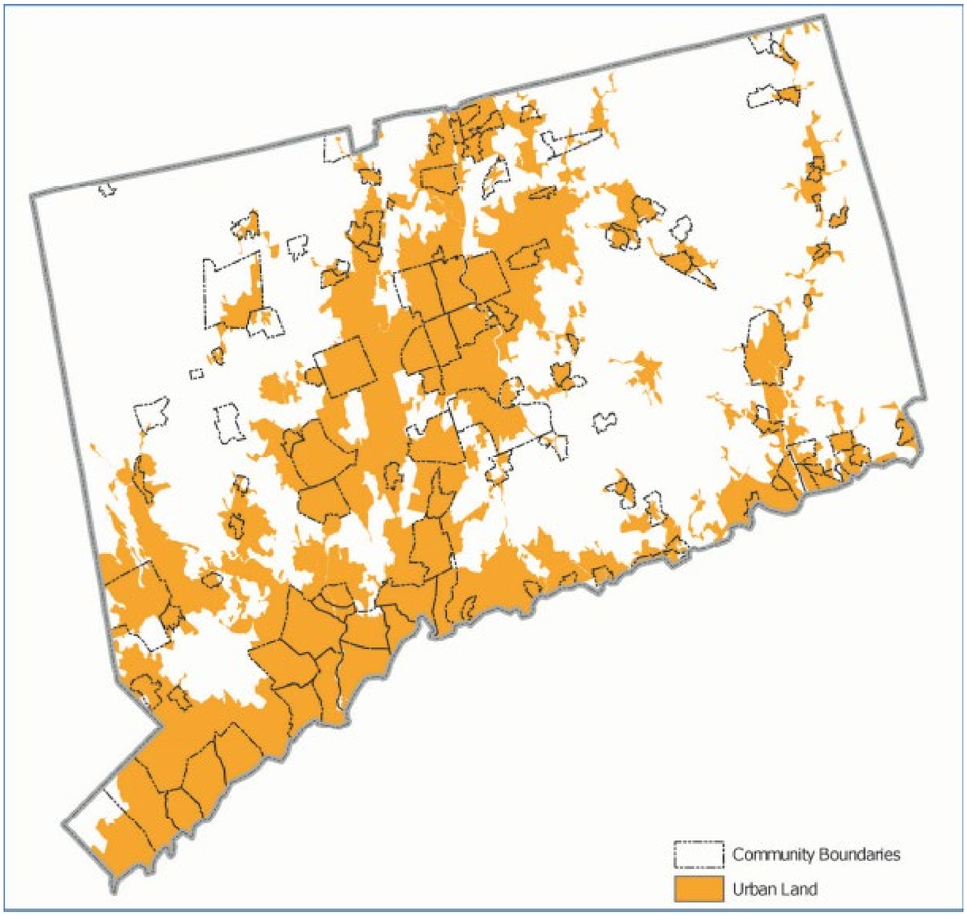
5-A.5.2 Defining Urban Forests

Urban forests: Urban forests are composed of a population of all trees within an area dominated by human settlement. To delimit the extent of an urban forest, the boundaries of the area of interest must be drawn. This boundary issue can be problematic, as people may conceive or describe "urban" differently. For clarity, this chapter defines urban forests as the population of all trees within urban areas and populated places ("communities") as defined by the U.S. Census Bureau based on population density and geopolitical boundaries.

Urban areas: The U.S. Census Bureau (2017) currently defines urban areas as "a densely settled core of census tracts and/or census blocks that meet minimum population density requirements, along with adjacent territory containing non-residential urban land uses as well as territory with low population density included to link outlying densely settled territory with the densely settled core." To qualify as an urban area, a territory must encompass at least 2,500 people, of whom at least 1,500 reside outside institutional group quarters. The Census Bureau identifies two types of urban areas: (1) urbanized areas of 50,000 or more people and (2) urban clusters of 2,500 to 50,000 people (U.S. Census Bureau, 2017). Urbanized areas and urban clusters were derived from census blocks and block groups with population densities of 1,000 people per square mile (386.1 people per square kilometer (250 acres)) in the core and 500 people per square mile (193.1 people per square kilometer) in the surrounding area.

Community areas: In addition to the urban areas described above, the Census Bureau delineates and labels incorporated and unincorporated concentrations of human populations such as cities, towns, villages, and hamlets as census-incorporated and designated places. Like urban areas, these "communities" also define areas where people reside but may include areas with lower population densities than those defined as urban.

Urban and community areas: The geographic areas of the urban and community definitions overlap (see figure 5A-5), and either or both are used to define urban forests as discussed in this chapter. The "urban area" designation is based on population density but may not follow the geopolitical boundaries of cities or towns that most people can relate to. The place or community boundaries follow these geopolitical borders, but often include both rural and urban areas within their limits. Thus, urban forest land may overlap with nonurban forest lands. That is, nonurban forested stands that are measured as part of other programs can exist within urban and community boundaries. Regional- or national-scale assessments of urban forest effects thus might double-count effects in forests. This overlap is estimated as 13.8 percent of urban area or 1.5 percent of forest area in the conterminous United States (Nowak et al., 2013) and is an important consideration for larger-scale assessments.



Source: U.S. Census Bureau, 2011.

Figure 5A-5. Urban and Community Areas in Connecticut

Section 5.2.4 focuses on assessing the carbon effects of urban and community trees and forests in the United States, but the tools it introduces can also be used in rural settings. Urban and community definitions may change from (decadal) census to census, while urban development and official borders change between censuses. Because the tools, models, and methods outlined in section 5.2.4 have been expanded to rural applications, users may draw their own boundaries or use varying combinations of the census geographies to assess their own areas of interest. For example, in rapidly urbanizing regions throughout the United States, users may wish to measure an area that they believe to be urbanizing but that is not officially defined as urban or community.

Trees within urban and community forests—which this chapter collectively calls urban forests—affect the carbon cycle by directly storing atmospheric carbon within the woody vegetation, as well as by affecting the local climate and thereby altering carbon emissions affected by local climatic conditions. Tree maintenance activities also affect carbon emissions in urban and community areas. In addition, urban wood may be harvested and used for an array of biomass-based products or disposed of as waste. For a true accounting of carbon effects, all these factors need to be considered. This chapter focuses on trees (defined as woody vegetation with a diameter of at least 1 inch, or 2.5 cm, dbh), but similar accounting could be conducted for other vegetation.

5-A.6 Carbon Estimation and Data Resources

Table 5A-3 provides a list of data resources and their descriptions. While some resources are described and used within this chapter, others are presented below for informational purposes only. Many of the static, previously published estimates of forest carbon attributes pulled from older databases and summarized in varying ways may still be useful for some applications where contemporary data may be lacking. However, it is beyond the purview of this report to reconcile all previous published estimates with those in this publication, which are meant to connect to emerging inventories and forest carbon quantification techniques.

Table 5A-3. Tool and Data Resources and Descriptions

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
USDA Forest Service Tools Based on FIA Program Data					
EVALIDator	USDA Forest Service FIA program	EVALIDator draws from FIA data to produce estimates with associated sampling errors for user-selected forest attributes: forest area, number of trees, biomass, volume, carbon, growth, removals, and mortality.	EVALIDator produces estimates for different carbon pools (e.g., total forest, aboveground biomass, belowground biomass, soil, standing dead trees). It reports on one attribute at a time, but also can produce ratio estimates (e.g., aboveground live carbon per forested acre). Report results are exported as HTML tables, maps (KML files that can be imported into Google Earth), or SQL code.	USDA Forest Service FIA data	Moderately advanced users who are familiar with FIA data and/or SQL.
Carbon OnLine Estimator (COLE)	USDA Forest Service Research and Development, National Council for Air and Stream Improvement, Inc.	COLE is currently unavailable, but there are ongoing efforts to relaunch it. The COLE suite of web applications allows users to create custom forest carbon outputs from information housed in the FIADB based on user-defined spatial boundaries.	The user defines a spatial area of interest using a map-based selection option. The user can modify the formatting and data retrieval parts of the query, including choosing variables of interest, units, sort options, and analysis functions (e.g., sum, mean, standard deviation). Tabular and graphical outputs can be downloaded in various formats, including Excel and JPEG.	USDA Forest Service FIA data	General audiences.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
Carbon Calculation Tool (CCT)	USDA Forest Service Research and Development, U.S. EPA	The CCT executable file runs on a PC and generates State-level annualized estimates of forest carbon stocks and fluxes.	CCT provides tabular summaries by State or national total for five forest ecosystem “reporting” pools from 1990 to present. It also outputs comprehensive pool reports for seven forest ecosystem pools. Both reports contain forest area, timberland area, and timberland live growing stock volume information. The summaries are exported as CSV files.	FORest CARBon Budget Model (FORCARB2) and USDA Forest Service FIA data	Users with an understanding of FIA data collection history and protocol will find it easier to choose between the estimation method options, but overall an easy-to-use tool for a wide audience.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
USDA Forest Service i-Tree suite of online tools and freely available software packages					
i-Tree Eco	USDA Forest Service, Davey Tree Expert Company, Arbor Day Foundation, Society of Municipal Arborists, International Society of Arboriculture, Casey Trees, SUNY College of Environmental Science and Forestry	The Eco downloadable desktop application quantifies the structure of, threats to, benefits of, and values provided by urban forests, including carbon stored and net carbon annually sequestered. It applies user-provided data collected from single trees, complete inventories, or randomly located plots. Users also have the option to collect and automatically upload their field data using the i-Tree Eco Mobile Data Collection system. At a minimum, users need to supply tree species and dbh data for complete inventory projects, and tree species, dbh, percent measured, and percent tree cover for sample-based inventories. Eco comes preloaded with location, species, and multi-year weather and pollution data for the United States and some other countries.	Eco has a variety of reporting options and outputs, from graphs and tables to complete autogenerated reports describing the benefits, effects, and values of an urban forest project. Carbon sequestration is estimated in weight and value per tree per year up to 100 years. The national Urban Forest Inventory and Analysis program inventories and monitors urban trees in more than 30 U.S. cities. For these cities, additional data collection is unnecessary and Eco software does not need to be run, since ecosystem services and values have already been catalogued online.	User-provided inputs combined with carbon estimation methods as described in i-Tree (2022c)	Government agencies, consultants, nonprofits, universities, researchers, volunteers, educators, and advocates undertaking projects ranging from small tree inventories to regional assessments. Users must supply their own inventory data and be able to import or enter field data into i-Tree Eco.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
i-Tree Landscape	USDA Forest Service, Davey Tree Expert Company, Arbor Day Foundation, Society of Municipal Arborists, International Society of Arboriculture, Casey Trees, SUNY College of Environmental Science and Forestry	i-Tree Landscape integrates national landscape and environmental data to support forest management and planning. It allows users to quantify carbon storage and annual sequestration, air pollution removal, hydrologic effects, and dollar value of each benefit for user-defined areas of interest. Users can explore tree canopy, land cover, and basic demographic information for their areas; see how planting trees will increase the benefits provided; and map areas for prioritizing tree planting efforts. Users can also explore local risks to people and forests due to climate change, wildfire, insects and diseases, air pollution, ultraviolet radiation, floods, urban development, and more, and can build tree planting alternatives based on local demographic data, tree cover information, and other variables.	The user creates a planting scenario and generates a PDF report summarizing the project area's planting priorities, tree benefits, and associated reference information.	2011 National Land Cover Database (NLCD), locally supplied high-resolution urban tree cover data (UTC HiRes), and USDA Forest Service FIA data	General audiences with limited data seeking information on total carbon stored and annual carbon sequestration as well as other ecosystem services.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
i-Tree County	USDA Forest Service, Davey Tree Expert Company, Arbor Day Foundation, Society of Municipal Arborists, International Society of Arboriculture, Casey Trees, SUNY College of Environmental Science and Forestry	i-Tree County is based on the data and methods of i-Tree Landscape. The tool allows users to quickly estimate carbon benefits and other ecosystem services and values from trees in an entire U.S. county or smaller area based on user-defined inputs. Users can examine 44 benefits of trees using this tool.	The user can generate a PDF report summarizing estimated benefits and values of the selected county's trees or a custom report based on user-supplied information including the project's area (in acres) and percent tree cover. In addition to the reports, data containing records of the 44 tree benefits for each U.S. county can be downloaded in several tabular and GIS formats.	2011 NLCD, locally supplied high-resolution urban tree cover data (UTC HiRes), and USDA Forest Service FIA data	See i-Tree Landscape description above.
i-Tree Design	USDA Forest Service, Davey Tree Expert Company, Arbor Day Foundation, Society of Municipal Arborists, International Society of Arboriculture, Casey Trees, SUNY College of Environmental Science and Forestry	i-Tree Design (formerly known as the National Tree Benefit Calculator) is a web-based tool for estimating the environmental benefits of individual or multiple trees at the parcel level. Benefits estimated by the calculator include carbon sequestration, decrease in stormwater runoff, air pollution capture and avoidance, and building energy use reduction. The tool works with a Google Maps interface where users view and analyze their property and structures in relation to established trees. Users can produce reports showing current carbon benefits and co-benefits and anticipated benefits from planting more trees.	Projects are saved as .dsgnprj files for future use and reports are exported as PDFs. The report shows total projected carbon benefits and co-benefits over the project's lifetime, benefits trees have provided since they were planted, and monetary benefits per tree.	Google Earth	Homeowners designing a tree planting project who wish to understand the past, current, and future environmental benefit of their trees. The tool is also used by educators, extension agents, landscape architects, energy companies, and tree nurseries.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
i-Tree MyTree	USDA Forest Service, Davey Tree Expert Company, Arbor Day Foundation, Society of Municipal Arborists, International Society of Arboriculture, Casey Trees, SUNY College of Environmental Science and Forestry	The MyTree mobile smartphone application quantifies carbon benefits and other ecosystem services and values for an individual tree or small population of trees. MyTree calculations are based on i-Tree Design. Tree benefits estimated include annual CO2 sequestration, stormwater interception, air pollution removed, energy savings, and avoided emissions, alongside monetary estimates for each benefit. MyTree is linked to the Trillion Trees campaign and the Nature Conservancy's Healthy Trees, Healthy Cities Tree Health Initiative. Trees entered in MyTree and planted for the Trillion Trees campaign are uploaded to the i-Tree Trillion Trees Map. MyTree shares citizen science data entered under Healthy Trees, Healthy Cities' tree health and pest detection protocols for advancing studies on urban tree health.	Users generate a tree benefits report based on details about the tree's location and characteristics.	Google Earth	General audiences with limited data. Designed for use on smartphones and tablets (via browser, without needing to install an app).

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
i-Tree Planting	USDA Forest Service, Davey Tree Expert Company, Arbor Day Foundation, Society of Municipal Arborists, International Society of Arboriculture, Casey Trees, SUNY College of Environmental Science and Forestry	i-Tree Planting (formerly known as the GHG Planting Calculator) is a web-based tool for estimating the environmental benefits of urban tree planting projects. It estimates benefits such as carbon sequestration, decrease in stormwater runoff, air pollution capture, and building energy use reduction.	i-Tree Planting calculates values associated with each tree group over the chosen timeframe based on the selected parameters. Users can save their i-Tree Planting projects and load them for later use. Users can export reports listing avoided building energy emissions and carbon sequestered along with associated monetary values over the project's lifetime.	USDA Forest Service, Davey Tree Expert Company, California Urban Forest Council, Urban Ecos, California Department of Forestry and Fire Protection	Urban foresters and other groups conducting tree planting projects.
i-Tree Canopy	USDA Forest Service, Davey Tree Expert Company, Arbor Day Foundation, Society of Municipal Arborists, International Society of Arboriculture, Casey Trees, SUNY College of Environmental Science and Forestry	i-Tree Canopy is a web-based tool for estimating canopy cover, land use, and associated benefits within a defined area of interest. Uses for the tool include establishing baselines for goal setting, determining areas for tree planting, monitoring change over time, and comparing tree canopy between neighborhoods and school districts. I-Tree Canopy estimates can be used in other i-Tree tools.	i-Tree Canopy project files are saved to the user's hard drive and shared with others working on joint projects. Output consists of a printable report with tables and figures summarizing the cover class type, percent cover, standard error of the cover type estimate, pollution removed, CO2 storage, annual CO2 sequestration rate, and monetary value for each source.	GIS data and Google Earth data	Municipal foresters, planners, and urban forestry coordinators, but the tool is also used by educators, volunteers, and neighborhood groups.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
i-Tree Harvest Carbon Calculator	USDA Forest Service, Davey Tree Expert Company, Arbor Day Foundation, Society of Municipal Arborists, International Society of Arboriculture, Casey Trees, SUNY College of Environmental Science and Forestry	The i-Tree Harvest Carbon Calculator (formerly known as the PRESTO Wood Calculator) is an online tool based on GTR-NE-343 methodologies and lookup tables for HWP pools. It automates GTR-NE-343 calculations and the selection of appropriate tables.	The tool produces tables and reports for four HWP pools based on harvest information supplied by the user: products in use, products in landfills, emitted with energy capture, and emitted without energy capture. The user can view, store, sort, and edit multiple stands for a project and save projects for future use. Stand tables are exported as CSV or Excel files.	GTR-NE-343	Land managers and landowners seeking estimates of postharvest carbon stored in wood products emanating from the lands they manage based on different harvest scenarios.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
USDA Forest Service					
GTR-NE-343	USDA Forest Service Research and Development	The GTR-NE-343 spreadsheet-based carbon calculator contains methods, sample calculations, and regional average tables (i.e., "lookup tables"). Carbon stocks and stock changes in GTR-NE-343 are based on regional averages.	The calculator can be used with or without user-supplied inventory data and provides estimates for average net annual additions to carbon in forests and forest products. Because the lookup tables characterize average carbon values over large areas, the actual carbon values for a stand or project area may differ and should not be used when conditions on a site vary widely. Users who have more specific data on any of the carbon pools, effects of previous land use, etc., may wish to modify figures based on local information and their distinct project needs. The tool features 51 major forest types across 10 geographic regions in the conterminous United States. Users identify the appropriate table for their forest type and look up (or modify) average regional carbon pool values. Separate sets of lookup tables are available for either reforestation/regrowth (i.e., stocks on forest land after clear-cut harvest) or afforestation management activities.	FORCARB2 model, Aggregate Timberland Assessment (ATLAS) model, and USDA Forest Service FIA data	Best suited for users who do not have inventory data and need initial carbon storage and emission estimates for reforestation and afforestation activities and estimates related to harvest, milling, and wood products.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
GTR-NRS-202 (https://www.nrs.fs.usda.gov/pubs/postprint/NRS-GTR-202/)	USDA Forest Service Northern Research Station	GTR-NRS-202 updates ecosystem carbon stock methodologies and estimates developed previously in GTR-NE-343. The new methodologies were developed in support of USDA GHG estimation guidelines for forestry and agriculture published in 2014 in response to direction in the 2008 Farm Bill. GTR-NRS-202 presents new methodologies, updated lookup tables, and information on differences between the new methodologies and those in GTR-NE-343.	The updated ecosystem carbon estimates are meant to be used to get reasonable estimates for major forest types in the conterminous United States. The lookup tables are not summaries of current FIA data and will not capture the inherent variability within forested ecosystems. The estimates are not intended to be used for tree planting scenarios and will likely not provide reliable estimates, at least in the early years following planting. Estimates for harvested wood carbon were not updated for GTR-NRS-202; users need to refer to GTR-NE-343 for these. To use the updated tables for ecosystem carbon, users select tables that best represent the forest type in their areas of interest. Users may apply linear interpolation calculations for values between lookup table values. Likewise, if users have local data for at least one carbon pool, they can substitute their data for values in the lookup tables.	FVS models	Meant for users who need reasonable estimates for major forest types in the conterminous United States.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
Forest Vegetation Simulator (FVS)	USDA Forest Service	The FVS suite of software incorporates a family of forest growth simulation models quantifying vegetation change in response to natural succession, disturbances, and management. It replaces ATLAS and FORCARB2 as the modeling framework used to derive the new GTR-NRS-202 carbon lookup tables. FVS recognizes all major tree species and can simulate nearly any type of management or disturbance at any time during the simulation.	FVS consists of a standard model and four model extensions, including the Fire and Fuels Extension (FFE). FFE has a carbon submodel, which allows users to produce carbon reports for ecosystem and HWP pools. A climate extension (Climate-FVS) for the western United States can be used to consider the effects of climate change on forested ecosystems.	FVS Source Code Project and user-supplied inventory data	Due to the complexity of the models and the ability to adjust many user-defined settings, learning FVS requires significant time before first-time users can generate outputs.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
Harvested Wood Product Carbon Storage Calculator (HWP Carbon Calculator)	USDA Forest Service	This tool is an online application currently being recoded. Plans are in place to transfer the code base to a USDA Forest Service server, after which the tool will be publicly available online. The HWP Carbon Calculator allows users with yearly harvest data in CCF or MBF and timber product ratios to generate graphics and tables for various measures of carbon storage and carbon emissions. There is a CAL FIRE and Oregon Department of Forestry version of this model, modified from the original USFS model that is currently available online.	Carbon storage outputs include annual harvest and timber product output, annual carbon stocks broken into products in use and solid waste disposal systems, and annual net change in carbon stocks. Carbon emission outputs include annual and total cumulative carbon emitted with and without energy capture.	Multiple sources, including GTR-NE-343, Skog (2008), FPL-GTR-199, McKeever (2009), Skog and Nicholson (2000), and U.S. EPA WARM (U.S. EPA, 2020b)	National Forest System employees produce estimates for the entire National Forest System using USDA annual cut-sold data and support State partners using timber product output data.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
Rangeland Carbon Tools	USDA Forest Service, Research and Development	*This tool is under production.* Since no existing USDA Forest Service tool can quantify carbon benefits on nonforest landscapes in the United States, research is underway to provide spatially explicit estimates of carbon in aboveground biomass and SOC for U.S. rangelands. The methods are being adapted based on results from a USDA Forest Service Research Note.	Outputs include estimates for existing nonforest vegetation height, type, and cover; biomass estimates for species assemblages; expanded biomass estimates from stems per unit area to biomass per unit area; and SOC estimates.	LANDFIRE data, Rangeland Vegetation Simulator, Domke et al. (2017), Cao et al. (2019), and FIA forest carbon estimates	National Forest System employees and other land managers.
Resource Planning Act (RPA) Assessment carbon projections	USDA Forest Service, Research and Development	The RPA Assessment includes projections of carbon stocks and fluxes based on FIA data and future climate and socioeconomic scenarios. The carbon projections move the FIA inventory forward in time as influenced by shifts in land use, climate, and demand for roundwood. This keeps both official USDA Forest Service carbon estimates and projections consistent with the FIA inventory.	The Land Use Change model projects future changes among croplands, forests, pastures, rangelands, and developed uses. The Forest Dynamics model projects carbon stock transfers associated with land-use change. The Forest Dynamics model also projects carbon stocks and stock changes for persistent forest land, accounting for forest aging, disturbance effects, climate affects, and forest management. The Forest Resource Outlook Model (FOROM) projects HWP and solid waste disposal site carbon stock and stock change based on inputs including FIA timber product output monitoring data, Food and Agriculture Organization data, and proprietary industry data sources.	RPA Forest Dynamics model, RPA Land Use Change model, FOROM, and Food and Agriculture Organization data	The RPA Assessment's carbon stock and stock change projections are not available as software or an online tool. They are developed by USDA Forest Service scientists and presented in RPA Assessment reports.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
Canadian Forest Service					
The Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3)	The Canadian Forest Service	The CBM-CFS3 wide-ranging decision support tool models forest carbon dynamics at stand and landscape levels for most forest types and geographic regions within Canada. Users can calculate past, present, and future forest ecosystem carbon stocks and stock changes under user-determined forest management scenarios. By default, the database behind the CBM-CFS3 comes with administrative and ecological names and parameters for Canadian jurisdictions and forest ecosystems. However, it can be re-parameterized to apply to jurisdictions and forest ecosystems in other countries. The Canadian Forest Service has also produced a variety of HWP C models that can be used in conjunction with CBM-CFS3 or with harvest data as a stand-alone exercise.	Users can customize model inputs and projects to incorporate different management activities, disturbance types and events, land-use change activities, growth curves, transition rules, and climate projections (temperature only). Assumption Composer tools in the model permit users to modify default project assumptions (or create new assumptions tied to alternate data or parameters), such as growth and yield, stand initialization, growth multipliers, and volume-to-biomass conversion, to simulate a wide range of modeled scenarios for the same imported forest inventory. The model simulates forest ecosystem carbon pools required under the Kyoto Protocol, including aboveground biomass, belowground biomass, litter, dead wood, and SOC using IPCC gain–loss carbon accounting methods.	Carbon Budget Modelling Framework for Harvested Wood Products model and Archive Index Database	Learning the CBM-CFS3 software requires an investment of time for a first-time user to understand the model and generate outputs. A detailed 348-page user guide is available from The Canadian Forest Service.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
Tools produced by nongovernment entities					
U.S. Community Protocol's Land Emissions and Removals Navigator (LEARN) tool (https://icleiusa.org/LEARN/)	ICLEI, in collaboration with the World Resources Institute's Global Forest Watch and the Woodwell Climate Research Center through funding from Doris Duke Charitable Foundation and the Climate and Land Use Alliance	This interactive web mapping tool was created to help U.S. communities estimate the local GHG impacts of their forests and trees. It allows counties and communities to develop a baseline and monitoring inventory of carbon stocks and stock changes in forests and trees outside forests. The tool directs users to i-Tree for working with high-resolution images or aerial photos, and to an offline harvested wood calculator if needed.	The tool calculates baseline emissions and removals for a customizable period of time at the community or county level from forests remaining forests; land-use change; and disturbances including harvest, fire, insects, and wind. Outputs are available as a full PDF report as well as a manipulatable Excel table.	FIA program data, data used for the U.S. EPA annual GHG reports, data in the previous version of these USDA guidelines, NLCD data from the U.S. Geological Survey, and NLCD tree canopy cover products from the USDA Forest Service	This tool is freely available to the public. It is simple to use and requires very little input data from users. Users with GIS skills can upload a shapefile to customize the area of interest.

Tool/Data Source Name	Tool Developer	Tool Description/Use	Tool Outputs	Underlying Data Source(s)	Target Audience and Skill Level
Measurement Reporting and Verification (MRV) Toolkit (https://www.goeslab.us/forest-carbon-mrv-tool.html)	Michigan State University	This interactive online software can be used to develop site-specific emission factors from forest inventories using a library of allometric equations and activity data from remote sensing or land-use change data. It produces estimates of emissions and removals for a selection of land use and silviculture situations or scenarios, either as a single practice or as a sequence of linked practices. It supports a complete statistical allocation of a field-based sample plot frame for a forest inventory, or a more simplified use of default values which circumvents the need of a more resource-intensive forest inventory. The MRV Toolkit has a web-mapping interface that allows users to draw project boundaries, parcels or strata within the project, and sample plots on a digital map or other image.	Outputs from this toolkit include two main types of reporting products. The first is estimates of carbon stocks from field inventories at the plot, strata, and project or property levels. The second is reports of calculations using the carbon inventories in chained scenarios of land-use change for the project area to estimate a range of emissions and removals. The toolkit manages all inventory data at the tree level and helps users develop emission factors. It can also use Tier 1 and Tier 2 data, as well as any default values the user provides. The toolkit provides a spatial estimate of the plot allocation for levels of precision and contains an allometric equation library and builder.	Underlying data include all IPCC default values and any Tier 1, 2, or 3 data provided by the user. The toolkit is primarily used with a project or site-specific carbon inventory. All pools are included, but most tools support the live biomass estimation and management.	The target audience is broad, from landowners to professionals. Users need some training and experience with the toolkit. It is suitable for managing data for any international IPCC-compliant project or carbon project registry with verifiers.

NA = Not applicable

5-A.7 Current Status and Future Prospects for Remote Sensing Measurement of Forest Carbon

Within national or regional GHG inventories, remote sensing has been a conventional way to get activity data to quantify the scale of land use and land-use change, though additional information may be needed to attribute drivers of land-use change and/or to determine whether it is a land cover or land-use change (see box 5-1). New platforms are being deployed that are increasing the spatial resolution of these remote sensing systems. These higher resolution products are making remote sensing methods more applicable and practical for smaller stands of forests, including small clusters of trees outside forests. Most of these products are aimed at regional applications for extremely large forest areas or mapping at the scale of counties, States, provinces, or continents. For farm-scale or individual project parcel applications, finer-resolution remote sensing data are needed. In practical terms, field inventory and GIS mapping are still the best practice for entity-scale applications, where properties are 1 square kilometer or smaller.

There are also several sources of up-to-date data that can be interactively traced for updating parcel land-use change using online GIS tools, such as the USDA Cropland Data Layer or Google Maps. Increasingly, commercial vendors are providing web-based mapping tools for overlaying current aircraft or very-high-resolution satellite imagery. Although commercial satellite data are now available at the spatial resolution of aerial photos—as fine as 30 centimeters—they can be expensive for an individual landowner. It is becoming more common for organizations or county governments and organizations to bundle data from several projects across a region, which brings down monitoring costs for individual landowners. Likewise, as organizations look to bundling several properties or parcels, the value of remote sensing data to cover large areas at one time increases. Google Maps, Bing Maps, and other similar platforms offer very-high-resolution image data, at the scale of 0.3 to 3 meters, readily available in a customer-facing form. These platforms present one simple way to informally and interactively view and map parcels and stands of trees on properties.

While methods for using remote sensing for activity data are well established, methods for using it to quantify the carbon stocks of the classes of forest and land-use change are less advanced (e.g., for developing emission factors). Although this field has advanced considerably, remote sensing measurement of tree carbon is currently in a research and development stage for use at the site or parcel scale. Large-scale (regional and continental), coarse-resolution methods have been developed, albeit with various degrees of uncertainty and site-specificity. In the coming years, advancements in very-high-resolution satellite remote sensing, coupled with machine learning, will likely enable direct measurement of carbon stocks. This includes high-spatial-resolution LiDAR, and satellites such as the GEDI mission.

5-A.8 Usage Notes on the Excel Workbook

The Excel workbook is paramount for the methods presented in this chapter. To help facilitate the development of approaches that open forest carbon markets to small parcel owners and/or underserved communities, this revised report includes a Level 1 approach that provides an initial estimate of forest carbon baseline scenario and potential effects of management interventions combining advances in forest ecosystem carbon monitoring, HWP accounting, and fire simulations (wildfire and prescribed). The Excel workbook serves a dual role as a “development workspace” for forest scientists to vet accounting logic and elucidate future refinements while providing basic outputs that the target audience could use immediately. The longer term vision is that with continued research and development investments, the Excel workbook accounting logic could be refined and migrated to a geospatial environment for more robust carbon estimation of parcels following advances in small area estimation, and more dynamic alignment between the tool and Federal data sources (e.g., FIA surveys and remotely sensed information) could be empowered via partners/communities (e.g., open-source code such as R APIs). Through increasing the transparency of accounting logic, data inputs via open-source code, and documentation of methods, it is expected that the leverage provided by USDA partners (e.g., the Natural Climate Solution marketplace, NGOs, States) will accomplish more than the Federal Government alone. Therefore, the Excel workbook is more than a tool—it is transparent accounting logic that can be built upon by the collective forest carbon science/user community in the future.

Appendix 5-B: Method Documentation

5-B.1 Silviculture Practices and Treatments

5-B.1.1 Rationale for Method

These guidelines' use of a Level 1 approach for quantifying impacts from silvicultural practices reflects the standard gain–loss approach to GHG inventories. As discussed in appendix 5-A.1.2., this approach is commonly favored where forest inventories do not exist and relies on published literature or other sources of credible data to assign emissions or carbon removal rates (i.e., emission factors or removal factors) to a measurement or estimate of the magnitude of human activity resulting in emissions or carbon removals (i.e., activity data).

The selection of silvicultural practices was limited to reforestation (natural regeneration or assisted regeneration/planting), extended rotation, and avoided deforestation because they are broadly understood and practiced across U.S. landscapes, their impacts are relatively straightforward to quantify given available data, and the ways in which they sequester additional carbon are well understood. These activities' ecosystem-side impacts could be estimated by combining user-supplied activity data with summarized ecosystem carbon stocks and annualized removal factors (i.e., carbon accrual/stock change), which could be generated using data collected from the FIA's network of permanent plots from across the continental United States (Burrill et al., 2021).

Summarizing these data by U.S. region, forest type group, age class (20-year classes), and stand origin (planted/not planted) yielded emission/removal factors that comprehensively reflect most U.S. forest types and estimate the annual accruals or potential emissions from the selected activities at a scale relevant to entities. This approach offers notable benefits, including the following:

- It applies FIA data to render generalized rates of annual carbon accruals for both planted and naturally regenerated forests across all major U.S. forest types using the NSVB estimators[10] (Westfall et al., 2023) launched in September 2023.
- Drawing from the latest, empirically derived FIA program data (i.e., plot remeasurement data) allows the lookup table values to reflect contemporary forest ecosystem carbon stocks and change, which may be particularly relevant in light of climate-induced changes being observed across U.S. landscapes (Domke et al., 2020).

5-B.1.2 Technical Documentation

Lookup Tables for Silvicultural Practices

The FIA program maintains an extensive array of permanent inventory plots across all land of the United States, with remeasurement generally occurring every 5 to 10 years. The granular forest inventory data are publicly available through a database system known as the FIADB, recently updated to render carbon estimates reflecting the NSVB estimators. The most current information available for each of the 48 conterminous States (typically 6 to 18 months after a panel of inventory plots have been completed within any given State), along with standard FIA estimation routines, was used to generate the lookup tables used in the Excel workbook. Lookup tables were partitioned by certain stand classification variables that allow the user to customize the information to their

[10] https://www.fs.usda.gov/research/programs/fia/nsvb

specific stand. The user must provide values for each of the following classification variables, which are then matched to the corresponding FIA carbon density and flux estimates in the lookup tables:

- Region (see figure 5-4)
- Forest type group (see table 5B-1)
- Stand origin (planted or natural)
- Stand age class (20-year increments to 100 years, then 100+)

The FIADB defines forest type groups by the field "typgrpcd," or forest type group in its condition (COND) table (Burrill et al., 2021). Stand origin ("stdorgcd" in the COND table), identifies stands with clear evidence of artificial regeneration; otherwise, natural regeneration is assumed. Stand age classes ("stdage" in the COND table) are divided into six classes: 0–20, 21–40, 41–60, 61–80, 81–100, and 100+ years. The Excel workbook allows for the user to select an additional class, "Unknown," for any combination of the forest type group, stand origin, age class variables to reflect cases when the user lacks knowledge about the stand being evaluated. Appropriately area-weighted summaries are calculated for all combinations of unknown stock and removal factor values for the stand parameters. Furthermore, each forest type group was reclassified into one of three additional classes—softwood, hardwood, or woodland—and these were used to reflect a user's limited knowledge about the species composition of the stand.

Population-based ratio estimates were generated using FIA estimation techniques to produce average values for carbon density and change components (Westfall et al., 2023). Estimation methods and FIA source table information for generating the lookup tables are contained in SQL scripts used to query and summarize the FIA data, and will accompany these guidelines.

The live tree or standing dead tree carbon stock tables provide carbon density (tons carbon per acre) for trees (≥1 inch dbh) based on the FIADB TREE table's fields "carbon_ag" or "carbon_bg." For each combination of the stand classification variables, mean carbon density is calculated as the quotient formed by the division of the estimate of total carbon stock by the estimate of forest land area for each classification variable combination. The components of gross growth that are used to compute carbon flux in the Excel workbook include survivor growth and ingrowth, and are defined in Westfall et al. (2022) and Pugh et al. (2018). The lookup tables thus contain values of change (tons of carbon change per acre per year) from these components and provide the information that the Excel workbook needs to generate estimates of carbon flux. Mortality is not subtracted: dead trees are assumed to remain in the stand and eventually convert to the DDW pool, which will eventually decay.

In addition to live and dead aboveground and belowground tree carbon, the lookup tables summarize the additional forest ecosystem carbon stocks associated with DDW and litter partitioned by each combination of the stand classification variables. SOC was not included in the annual carbon flux (i.e., emission or removal factors) because current FIA sampling protocols are not sufficient to detect soil carbon stocks and changes, particularly as those changes relate to the impact of specific forest management activities. Similarly, change in standing dead (aboveground or belowground) were not included in change calculations for reasons mentioned in the text. All nontree stock estimates are based on values provided in the FIADB COND table (Burrill et al., 2021). Carbon stock density values (tons carbon per acre) are average values according to region, type, origin, and age class, similar to the approach for tree carbon density. However, the estimates of change for these COND table values are based on average annual net stock change on remeasured plots that are identified as forest at both time 1 and time 2.

The logic behind applying factors from FIA data summaries is as follows.

In the Excel workbook, the user selects (via dropdown menus) the combination of the stand classification variables that corresponds with their knowledge of the stand being evaluated, also providing the acreage of the stand. When values for a user's choice do not exist (i.e., the selected combination of classification variables does not exist in the lookup tables), aggregated values are used as described above. When this occurs, the tool extracts the appropriate carbon density or flux value from the lookup table and applies equation 5B-1 to estimate the total stock, which is then used in equation 5-5. The Excel workbook then generates the Removal Factor, as shown in equation 5B-2; this is used in equation 5-1.

Equation 5B-1: Carbon Stock for Silvicultural Practices

$$Total\ CS_{,rtpa} = (CD_{AGL,rtpa} + CD_{AGD,rtpa} + CD_{BGL,rtpa} + CD_{BGD,rtpa} + CD_{DDW,rtpa} + CD_{L,rtpa} + C_{SOC,rtpa})$$

Where:

Total CS	=	carbon stocks (sum of all carbon pools) (U.S. tons/acre)
CD	=	carbon stocks (U.S. tons/acre)
AGL	=	aboveground live carbon
AGD	=	aboveground dead carbon
BGL	=	belowground live carbon
BGD	=	belowground dead carbon
DDW	=	down dead wood
L	=	litter
SOC	=	soil organic carbon
r	=	region
t	=	forest type group
p	=	planted/natural code
a	=	age class

Equation 5B-2: Change in Carbon Stock from Growth (i.e., Removal Factor)

$$RF_{rtpa} = (\Delta CD_{AGL,T_1,rpta} + \Delta CD_{BGL,T_1,rpta} + \Delta CD_{DDW,T_1,rpta} + \Delta CD_{L,T_1,rpta})$$

Where:

RF	=	sum of all change in carbon stocks (U.S. tons/acre/year)
ΔCD	=	annualized carbon stock change between FIA remeasurement cycles (U.S. tons/acre/year)
AGL	=	aboveground live carbon
BGL	=	belowground live carbon
DDW	=	down dead wood
L	=	litter
r	=	region
t	=	forest type group
p	=	planted/natural code
a	=	age class

Table 5B-1 lists classification variables used in constructing the lookup tables that contain stock and growth factors. Lookup tables contain every combination of these variables that exist in the FIADB in the latest full cycle of inventory data. Values in italics were created for scenarios when the user has limited or no knowledge of the stand characteristics. State groupings for the "region" variable can be found in the provided SQL code and seen in figure 5-4.

Table 5B-1. Classification Variables for the Stocking and Growth Factor Lookup Tables

Region	Forest Type Group		Planted/ Natural Code	Age Class
▪ Central States ▪ Great Plains ▪ Northeast ▪ Northern Lake States ▪ Pacific Northwest Eastside ▪ Pacific Northwest Westside ▪ Pacific Southwest ▪ Rocky Mountain North ▪ Rocky Mountain South ▪ South Central ▪ Southeast	▪ White/red/jack pine group ▪ Spruce/fir group ▪ Longleaf/slash pine group ▪ Loblolly/shortleaf pine group ▪ Other eastern softwoods group ▪ Pinyon/juniper group ▪ Douglas-fir group ▪ Ponderosa pine group ▪ Western white pine group ▪ Fir/spruce/ mountain hemlock group ▪ Lodgepole pine group ▪ Hemlock/Sitka spruce group ▪ Western larch group ▪ Redwood group ▪ Other western softwoods group ▪ California mixed conifer group	▪ Exotic softwoods group ▪ Other softwoods group ▪ Oak/pine group ▪ Oak/hickory group ▪ Oak/gum/cypress group ▪ Elm/ash/ cottonwood group ▪ Maple/beech/birch group ▪ Aspen/birch group ▪ Alder/maple group ▪ Western oak group ▪ Tanoak/laurel group ▪ Other hardwoods group ▪ Woodland hardwoods group ▪ Tropical hardwoods group ▪ Exotic hardwoods group ▪ Nonstocked ▪ Hardwood ▪ Softwood ▪ Woodland ▪ *Unknown*	▪ Planted ▪ Natural ▪ *Unknown*	▪ 0–20 years ▪ 21–40 years ▪ 41–60 years ▪ 61–80 years ▪ 81–100 years ▪ 100+ years ▪ *Unknown*

5-B.2 Harvested Wood Products

5-B.2.1 Rationale for Method

This highest accessibility (Level 1) approach was chosen because it is less complicated and more flexible than existing models and is a suitable model to represent the amount of carbon stored in products in use and in landfills, with their associated emissions.

When forest landowners harvest trees for wood products, a portion of the wood carbon ends up in solid wood products or paper products in end uses, and eventually in landfills. It can remain stored for years or decades. In the past, USDA Forest Service researchers used the WOODCARB II model to estimate aggregate U.S. HWP carbon storage. This modeling system started with national wood consumption to ascertain domestic production. More recently, the National Forest System and State entities have used newer models to adhere to the IPCC production approach at the subnational level (including the USDA Forest Service HWP Carbon Calculator and a similar California variant). The USDA Forest Service built these tools to expand and improve WOODCARB II's calculations, leveraging various fundamental data sources such as Smith et al. (2006), Skog (2008), McKeever (2009) and McKeever and Howard (2011).

The USDA Forest Service built and customized these models to handle actual available data, such as annual cut and sold reports from each national forest and timber product output data (in 40 categories) for States. There is a major point of distinction between the guidance and calculators described below and these more advanced models. The chosen methods are intended for landowners and land managers at the entity level who may not have access to this information about their harvests and how the harvested material will be used. In addition, the more advanced models can combine sequential harvests and multiple vintage year results into cumulative storage and emissions through time. They have more detailed end use allocations, along with a wider range of data on end use half-lives and end-of-life dispositions than prior models—such as splitting out burning with and without energy capture. The time series of recycling and other disposition ratio estimates have also been updated with the U.S. EPA's WARM (U.S. EPA, 2020b) data from 2018 in the USDA Forest Service HWP Carbon Calculator. Moreover, these later models now provide emission estimates in CO_2-eq, recognizing the carbon does not exist as CO_2 in trees or wood products but will end up as CO_2 in the atmosphere. Nonetheless, the emissions modeling could certainly be improved to account for the range of gases produced at various stages of burning and decay.

Ideally, a Level 3 tool would seamlessly integrate ecosystem and HWP modeling with robust estimates and be able to model single-harvest or entire-harvest records with projected future harvests.

5-B.2.2 Technical Documentation

This section provides the detailed technical documentation for methods and calculators described in section 5.2.2. Tables 5B-2 through 5B-6 list factors and fractions used within the HWP lookup tables. The calculator demonstrations describe the growing stock calculator, harvest carbon calculator, and potential substitution calculator, which work together in the Excel workbook to produce results.

Table 5B-2. Factors to Calculate Carbon in Growing Stock Volume: Softwood Fraction, Sawtimber-Size Fraction, and Specific Gravity by Region and Forest Type Group[a]

Region	Forest Type	Fraction of Growing-Stock Volume That Is Softwood[b]	Fraction of Softwood Growing-Stock Volume That Is Sawtimber-Size[c]	Fraction of Hardwood Growing-Stock Volume That Is Sawtimber-Size[c]	Specific Gravity[d] of Softwoods	Specific Gravity[d] of Hardwoods
Northeast	Aspen-birch	0.247	0.439	0.330	0.353	0.428
	Elm-ash-cottonwood	0.047	0.471	0.586	0.358	0.470
	Maple-beech-birch	0.132	0.604	0.526	0.369	0.518
	Oak-hickory	0.039	0.706	0.667	0.388	0.534
	Oak-pine	0.511	0.777	0.545	0.371	0.516
	Spruce-fir	0.870	0.508	0.301	0.353	0.481
	White-red-jack pine	0.794	0.720	0.429	0.361	0.510
Northern Lake States	Aspen-birch	0.157	0.514	0.336	0.351	0.397
	Elm-ash-cottonwood	0.107	0.468	0.405	0.335	0.460
	Maple-beech-birch	0.094	0.669	0.422	0.356	0.496
	Oak-hickory	0.042	0.605	0.473	0.369	0.534
	Spruce-fir	0.876	0.425	0.276	0.344	0.444
	White-red-jack pine	0.902	0.646	0.296	0.389	0.473
Northern Prairie States	Elm-ash-cottonwood	0.004	0.443	0.563	0.424	0.453
	Loblolly-shortleaf pine	0.843	0.686	0.352	0.468	0.544
	Maple-beech-birch	0.010	0.470	0.538	0.437	0.508
	Oak-hickory	0.020	0.497	0.501	0.448	0.565
	Oak-pine	0.463	0.605	0.314	0.451	0.566
	Ponderosa pine	0.982	0.715	0.169	0.381	0.473
Pacific Northwest, East	Douglas-fir	0.989	0.896	0.494	0.429	0.391
	Fir-spruce-m.hemlock	0.994	0.864	0.605	0.370	0.361
	Lodgepole pine	0.992	0.642	0.537	0.380	0.345
	Ponderosa pine	0.996	0.906	0.254	0.385	0.513
Pacific Northwest,	Alder-maple	0.365	0.895	0.635	0.402	0.385
	Douglas-fir	0.959	0.914	0.415	0.440	0.426

Region	Forest Type	Fraction of Growing-Stock Volume That Is Softwood[b]	Fraction of Softwood Growing-Stock Volume That Is Sawtimber-Size[c]	Fraction of Hardwood Growing-Stock Volume That Is Sawtimber-Size[c]	Specific Gravity[d] of Softwoods	Specific Gravity[d] of Hardwoods
West	Fir-spruce-m.hemlock	0.992	0.905	0.296	0.399	0.417
	Hemlock-Sitka spruce	0.956	0.909	0.628	0.405	0.380
Pacific Southwest	Mixed conifer	0.943	0.924	0.252	0.394	0.521
	Douglas-fir	0.857	0.919	0.320	0.429	0.483
	Fir-spruce-m.hemlock	1.000	0.946	0.000	0.372	0.510
	Ponderosa pine	0.997	0.895	0.169	0.380	0.510
	Redwood	0.925	0.964	0.468	0.376	0.449
Rocky Mountain, North	Douglas-fir	0.993	0.785	0.353	0.428	0.370
	Fir-spruce-m.hemlock	0.999	0.753	0.000	0.355	0.457
	Hemlock-Sitka spruce	0.972	0.735	0.596	0.375	0.441
	Lodgepole pine	0.999	0.540	0.219	0.383	0.391
	Ponderosa pine	0.999	0.816	0.000	0.391	0.374
Rocky Mountain, South	Aspen-birch	0.297	0.766	0.349	0.355	0.350
	Douglas-fir	0.962	0.758	0.230	0.431	0.350
	Fir-spruce-m.hemlock	0.958	0.770	0.367	0.342	0.350
	Lodgepole pine	0.981	0.607	0.121	0.377	0.350
	Ponderosa pine	0.993	0.773	0.071	0.383	0.386
Southeast	Elm-ash-cottonwood	0.030	0.817	0.551	0.433	0.499
	Loblolly-shortleaf pine	0.889	0.556	0.326	0.469	0.494
	Longleaf-slash pine	0.963	0.557	0.209	0.536	0.503
	Oak-gum-cypress	0.184	0.789	0.500	0.441	0.484
	Oak-hickory	0.070	0.721	0.551	0.438	0.524
	Oak-pine	0.508	0.746	0.425	0.462	0.516
South Central	Elm-ash-cottonwood	0.044	0.787	0.532	0.427	0.494
	Loblolly-shortleaf pine	0.880	0.653	0.358	0.470	0.516
	Longleaf-slash pine	0.929	0.723	0.269	0.531	0.504
	Oak-gum-cypress	0.179	0.830	0.589	0.440	0.513

Region	Forest Type	Fraction of Growing-Stock Volume That Is Softwood[b]	Fraction of Softwood Growing-Stock Volume That Is Sawtimber-Size[c]	Fraction of Hardwood Growing-Stock Volume That Is Sawtimber-Size[c]	Specific Gravity[d] of Softwoods	Specific Gravity[d] of Hardwoods
	Oak-hickory	0.057	0.706	0.534	0.451	0.544
	Oak-pine	0.512	0.767	0.432	0.467	0.537
Weste	Pinyon-juniper	0.986	0.783	0.042	0.422	0.620
	Tankoak-laurel	0.484	0.909	0.468	0.430	0.459
	Western larch	0.989	0.781	0.401	0.433	0.430
	Western oak	0.419	0.899	0.206	0.416	0.590
	Western white pine	1.000	0.838	0.000	0.376	—

Source: Smith et al. (2006), table 4.

— = no hardwood trees in this type in this region.

[a] Estimates are based on survey data for the conterminous United States from FIADB (USDA Forest Service, 2005) and include growing stock on timberland stands classified as medium- or large-diameter stands. Proportions are based on volume of growing-stock trees.

[b] To calculate fraction in hardwood, subtract fraction in softwood from 1.

[c] Softwood sawtimber are trees at least 22.9 cm (9 in) dbh; hardwood sawtimber is at least 27.9 cm (11 in) dbh. To calculate fraction in less-than-sawtimber-size trees, subtract fraction in sawtimber from 1. Trees less than sawtimber-size are at least 12.7 cm (5 in) dbh.

[d] Average wood specific gravity is the density of wood divided by the density of water based on wood dry mass associated with green tree volume.

[e] West represents an average over all western regions for these forest types.

Table 5B-3. Regional Factors to Estimate Carbon in Roundwood Logs, Bark on Logs, and Fuelwood

Region[a]	Timber Type	Roundwood Category	Fraction of Growing-Stock Volume That Is Roundwood[b]	Ratio of Roundwood (Excluding Fuelwood) to Growing-Stock Roundwood Volume (Including Fuelwood)[c]	Ratio of Fuelwood to Growing-Stock Volume That Is Roundwood[c]	Ratio of Carbon in Bark to Carbon in Wood[d]
Northeast	SW	Sawlog	0.948	0.991	0.136	0.182
		Pulpwood		3.079		0.185
	HW	Sawlog	0.879	0.927	0.547	0.199
		Pulpwood		2.177		0.218
North Central	SW	Sawlog	0.931	0.985	0.066	0.182
		Pulpwood		1.285		0.185
	HW	Sawlog	0.831	0.960	0.348	0.199
		Pulpwood		1.387		0.218
Pacific Coast	SW	Sawlog	0.929	0.965	0.096	0.181
		Pulpwood		1.099		0.185
	HW	Sawlog	0.947	0.721	0.957	0.197
		Pulpwood		0.324		0.219
Rocky Mountain	SW	Sawlog	0.907	0.994	0.217	0.181
		Pulpwood		2.413		0.185
	HW	Sawlog	0.755	0.832	3.165	0.201
		Pulpwood		1.336		0.219
South	SW	Sawlog	0.891	0.990	0.019	0.182
		Pulpwood		1.246		0.185
	HW	Sawlog	0.752	0.832	0.301	0.198
		Pulpwood		1.191		0.218

Source: Smith et al. (2006), table 5.

SW = softwood, HW = hardwood.

[a] "North Central" includes the northern Prairie States and the northern Lake States; "Pacific Coast" includes the Pacific Northwest (west and east) and the Pacific Southwest; "Rocky Mountain" includes Rocky Mountain, north and south; and South includes the Southeast and South Central.

[b] Values and classifications are based on data in tables 2.9, 3.9, 4.9, 5.9, and 6.9 of Johnson (2001).

[c] Values and classifications are based on data in tables 2.2, 3.2, 4.2, 5.2, and 6.2 of Johnson (2001).

[d] Ratios are calculated from carbon mass based on biomass component equations in Jenkins et al. (2003), applied to all live trees identified as growing stock on timberland stands classified as medium- or large-diameter stands in the survey data for the conterminous United States from the FIADB (Alerich et al., 2005; USDA Forest Service, 2005). Carbon mass is calculated for boles from stump to 4-inch (10.2 cm) top, outside diameter.

Table 5B-4. Fraction of Each Classification of Industrial Roundwood (Primary Wood Products)[a]

Region	Category[b] SW/HW	Category[b] SL/PW	Softwood Lumber	Hardwood Lumber	Softwood Plywood	Hardwood Plywood[c]	Oriented Strandboard	Nonstructural Panels	Other Industrial Products	Wood Pulp	Fuel and Other Emissions
Northeast	SW	SL	0.391	0	0.004	0	0	0.020	0.083	0.072	0.431
		PW	0	0	0	0	0.010	0.016	0	0.487	0.487
	HW	SL	0	0.492	0	0.005	0	0.022	0.038	0.058	0.386
		PW	0	0	0	0	0.293	0.007	0	0.350	0.350
North Central	SW	SL	0.378	0	0	0	0	0.049	0.120	0.084	0.370
		PW	0	0	0	0	0.020	0.009	0	0.486	0.486
	HW	SL	0	0.458	0	0.006	0	0.013	0.044	0.064	0.415
		PW	0	0	0	0	0.361	0.009	0	0.315	0.315
Pacific Northwest, East	SW	All	0.422	0	0.069	0	0	0.001	0.001	0.144	0.363
Pacific Northwest, West	SW	SL	0.455	0	0.089	0	0	0.009	0.073	0.114	0.260
		PW	0	0	0	0	0	0	0	0.500	0.500
	HW	All	0	0.160	0	0.140	0	0.002	0	0.229	0.469
Pacific Southwest	SW	All	0.454	0	0	0	0	0.040	0.036	0.145	0.325
Rocky Mountain	SW	All	0.402	0	0.054	0	0	0.033	0.062	0.153	0.296
Southeast	SW	SL	0.350	0	0.076	0	0	0.027	0.054	0.129	0.364
		PW	0	0	0	0	0.103	0.004	0	0.447	0.447
	HW	SL	0	0.455	0	0.006	0	0.049	0.012	0.087	0.391
		PW	0	0	0	0	0.180	0.002	0	0.409	0.409
South Central	SW	SL	0.324	0	0.130	0	0	0.019	0.023	0.133	0.371
		PW	0	0	0	0	0.135	0.006	0	0.430	0.430
	HW	SL	0	0.434	0	0.023	0	0.025	0.003	0.102	0.413
		PW	0	0	0	0	0.160	0.001	0	0.419	0.419
West[d]	HW	All	0	0.039	0	0.301	0	0.015	0.066	0.147	0.432

Source: Smith et al. (2006), table D6.

[a] Data based on Adams and others (2006).

[b] SW/HW = softwood/hardwood, SL/PW = saw log/pulpwood. Saw log includes veneer logs.

[c] Hardwood plywood fractions are pooled with nonstructural panels when allocating roundwood to the primary products listed in tables 8 and 9 of Smith et al. (2006).

[d] West includes hardwoods in Pacific Northwest, East; Pacific Southwest; Rocky Mountain; North; and Rocky Mountain, South.

Table 5B-5. Total Carbon Fraction Remaining in End Uses: Exponential Function

Year After Production	Softwood Lumber	Hardwood Lumber	Softwood Plywood	Hardwood Plywood	Oriented Strandboard	Nonstructural Panels	Miscellaneous Products	Paper
0	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
1	0.917	0.881	0.921	0.914	0.930	0.914	0.887	0.895
2	0.887	0.820	0.894	0.880	0.911	0.880	0.828	0.800
3	0.858	0.765	0.868	0.848	0.892	0.848	0.773	0.716
4	0.831	0.716	0.844	0.818	0.874	0.818	0.722	0.640
5	0.806	0.671	0.821	0.789	0.857	0.789	0.674	0.573
6	0.782	0.631	0.799	0.762	0.841	0.762	0.629	0.512
7	0.760	0.594	0.778	0.736	0.825	0.736	0.587	0.458
8	0.739	0.561	0.758	0.711	0.810	0.711	0.548	0.410
9	0.719	0.531	0.740	0.688	0.796	0.688	0.512	0.367
10	0.700	0.503	0.722	0.665	0.782	0.665	0.478	0.328
11	0.681	0.478	0.704	0.644	0.768	0.644	0.446	0.293
12	0.664	0.455	0.688	0.624	0.755	0.624	0.417	0.262
13	0.648	0.433	0.672	0.604	0.742	0.604	0.389	0.235
14	0.632	0.414	0.657	0.586	0.730	0.586	0.363	0.210
15	0.617	0.395	0.643	0.568	0.718	0.568	0.339	0.188
16	0.603	0.378	0.629	0.551	0.707	0.551	0.317	0.168
17	0.589	0.362	0.615	0.535	0.696	0.535	0.296	0.150
18	0.576	0.347	0.602	0.520	0.685	0.520	0.276	0.134
19	0.563	0.334	0.590	0.505	0.674	0.505	0.258	0.120
20	0.551	0.321	0.578	0.490	0.664	0.490	0.241	0.108
21	0.540	0.308	0.566	0.477	0.654	0.477	0.225	0.096
22	0.529	0.297	0.555	0.464	0.645	0.464	0.210	0.086
23	0.518	0.286	0.544	0.451	0.635	0.451	0.196	0.077
24	0.507	0.276	0.534	0.439	0.626	0.439	0.183	0.069
25	0.497	0.266	0.524	0.427	0.617	0.427	0.171	0.062
26	0.488	0.257	0.514	0.416	0.608	0.416	0.159	0.055
27	0.478	0.248	0.504	0.405	0.600	0.405	0.149	0.049
28	0.469	0.240	0.495	0.395	0.591	0.395	0.139	0.044
29	0.460	0.232	0.486	0.385	0.583	0.385	0.130	0.039

Year After Production	Softwood Lumber	Hardwood Lumber	Softwood Plywood	Hardwood Plywood	Oriented Strandboard	Nonstructural Panels	Miscellaneous Products	Paper
30	0.452	0.225	0.477	0.375	0.575	0.375	0.121	0.035
31	0.444	0.218	0.469	0.366	0.568	0.366	0.113	0.032
32	0.436	0.211	0.461	0.357	0.560	0.357	0.106	0.028
33	0.428	0.204	0.453	0.348	0.553	0.348	0.099	0.025
34	0.421	0.198	0.445	0.340	0.545	0.340	0.092	0.023
35	0.413	0.192	0.437	0.332	0.538	0.332	0.086	0.020
36	0.406	0.186	0.430	0.324	0.531	0.324	0.080	0.018
37	0.399	0.181	0.423	0.316	0.524	0.316	0.075	0.016
38	0.393	0.176	0.416	0.309	0.518	0.309	0.070	0.014
39	0.386	0.171	0.409	0.302	0.511	0.302	0.065	0.013
40	0.380	0.166	0.402	0.295	0.505	0.295	0.061	0.012
41	0.374	0.161	0.396	0.288	0.498	0.288	0.057	0.010
42	0.368	0.157	0.389	0.282	0.492	0.282	0.053	0.009
43	0.362	0.152	0.383	0.275	0.486	0.275	0.050	0.008
44	0.356	0.148	0.377	0.269	0.480	0.269	0.046	0.007
45	0.351	0.144	0.371	0.263	0.474	0.263	0.043	0.007
46	0.345	0.140	0.365	0.258	0.468	0.258	0.040	0.006
47	0.340	0.136	0.360	0.252	0.463	0.252	0.038	0.005
48	0.335	0.133	0.354	0.247	0.457	0.247	0.035	0.005
49	0.329	0.129	0.349	0.241	0.451	0.241	0.033	0.004
50	0.325	0.126	0.344	0.236	0.446	0.236	0.031	0.004
55	0.301	0.111	0.319	0.213	0.420	0.213	0.022	0.002
60	0.280	0.098	0.296	0.193	0.396	0.193	0.015	0.001
65	0.262	0.086	0.276	0.175	0.374	0.175	0.011	0.001
70	0.244	0.077	0.258	0.159	0.353	0.159	0.008	0.000
75	0.229	0.069	0.241	0.145	0.334	0.145	0.006	0.000
80	0.214	0.061	0.225	0.132	0.316	0.132	0.004	0.000
85	0.201	0.055	0.211	0.121	0.299	0.121	0.003	0.000
90	0.189	0.050	0.198	0.111	0.283	0.111	0.002	0.000
95	0.177	0.045	0.186	0.103	0.268	0.103	0.001	0.000
100	0.167	0.040	0.175	0.094	0.254	0.094	0.001	0.000

Year After Production	Softwood Lumber	Hardwood Lumber	Softwood Plywood	Hardwood Plywood	Oriented Strandboard	Nonstructural Panels	Miscellaneous Products	Paper
100-year average (years 0 to 99)	0.391	0.211	0.408	0.320	0.495	0.320	0.144	0.095

Table 5B-6. Total Carbon Fraction Remaining in SWDS: Exponential Function

Year After Production	Softwood Lumber	Hardwood Lumber	Softwood Plywood	Hardwood Plywood	Oriented Strandboard	Nonstructural Panels	Miscellaneous Products	Paper
0	—	—	—	—	—	—	—	—
1	0.067	0.096	0.064	0.069	0.056	0.069	0.091	0.085
2	0.091	0.145	0.085	0.096	0.072	0.096	0.138	0.159
3	0.114	0.189	0.106	0.122	0.087	0.122	0.182	0.223
4	0.135	0.228	0.125	0.146	0.101	0.146	0.223	0.278
5	0.155	0.263	0.144	0.169	0.114	0.169	0.261	0.326
6	0.174	0.295	0.161	0.190	0.127	0.190	0.297	0.366
7	0.192	0.324	0.177	0.211	0.139	0.211	0.330	0.401
8	0.208	0.350	0.193	0.230	0.151	0.230	0.360	0.430
9	0.224	0.373	0.207	0.248	0.162	0.248	0.389	0.455
10	0.239	0.395	0.221	0.266	0.173	0.266	0.415	0.475
11	0.253	0.414	0.234	0.282	0.184	0.282	0.440	0.492
12	0.266	0.432	0.247	0.298	0.194	0.298	0.462	0.506
13	0.279	0.448	0.259	0.313	0.204	0.313	0.484	0.517
14	0.291	0.463	0.271	0.327	0.213	0.327	0.503	0.525
15	0.302	0.477	0.282	0.341	0.222	0.341	0.521	0.532
16	0.313	0.489	0.292	0.354	0.231	0.354	0.538	0.536
17	0.323	0.501	0.303	0.366	0.239	0.366	0.554	0.540
18	0.333	0.512	0.312	0.378	0.248	0.378	0.569	0.541
19	0.342	0.522	0.322	0.389	0.255	0.389	0.582	0.542
20	0.351	0.531	0.331	0.399	0.263	0.399	0.595	0.541
21	0.360	0.540	0.339	0.410	0.271	0.410	0.606	0.540
22	0.368	0.548	0.348	0.419	0.278	0.419	0.617	0.538
23	0.376	0.556	0.356	0.428	0.285	0.428	0.627	0.535
24	0.384	0.563	0.363	0.437	0.292	0.437	0.636	0.532
25	0.391	0.569	0.371	0.446	0.298	0.446	0.645	0.529
26	0.398	0.576	0.378	0.454	0.305	0.454	0.652	0.525
27	0.405	0.582	0.385	0.462	0.311	0.462	0.660	0.521
28	0.411	0.587	0.391	0.469	0.317	0.469	0.666	0.516
29	0.418	0.592	0.398	0.476	0.323	0.476	0.672	0.512
30	0.424	0.597	0.404	0.483	0.329	0.483	0.678	0.507
31	0.429	0.602	0.410	0.490	0.334	0.490	0.683	0.502
32	0.435	0.606	0.416	0.496	0.340	0.496	0.688	0.498

Year After Production	Softwood Lumber	Hardwood Lumber	Softwood Plywood	Hardwood Plywood	Oriented Strandboard	Nonstructural Panels	Miscellaneous Products	Paper
33	0.440	0.610	0.422	0.502	0.345	0.502	0.692	0.493
34	0.446	0.614	0.427	0.508	0.350	0.508	0.697	0.488
35	0.451	0.618	0.433	0.514	0.355	0.514	0.700	0.484
36	0.456	0.622	0.438	0.519	0.360	0.519	0.704	0.479
37	0.460	0.625	0.443	0.524	0.365	0.524	0.707	0.474
38	0.465	0.628	0.448	0.529	0.370	0.529	0.710	0.470
39	0.469	0.631	0.452	0.534	0.375	0.534	0.712	0.466
40	0.474	0.634	0.457	0.539	0.379	0.539	0.714	0.461
41	0.478	0.637	0.462	0.543	0.384	0.543	0.717	0.457
42	0.482	0.640	0.466	0.548	0.388	0.548	0.719	0.453
43	0.486	0.642	0.470	0.552	0.392	0.552	0.720	0.449
44	0.490	0.645	0.474	0.556	0.397	0.556	0.722	0.445
45	0.494	0.647	0.478	0.560	0.401	0.560	0.723	0.442
46	0.497	0.649	0.482	0.564	0.405	0.564	0.725	0.438
47	0.501	0.651	0.486	0.567	0.409	0.567	0.726	0.435
48	0.504	0.653	0.490	0.571	0.413	0.571	0.727	0.431
49	0.508	0.655	0.493	0.574	0.416	0.574	0.728	0.428
50	0.511	0.657	0.497	0.577	0.420	0.577	0.728	0.425
55	0.526	0.665	0.513	0.592	0.438	0.592	0.731	0.411
60	0.539	0.672	0.528	0.605	0.454	0.605	0.732	0.400
65	0.551	0.677	0.541	0.616	0.469	0.616	0.732	0.391
70	0.562	0.682	0.553	0.625	0.483	0.625	0.731	0.383
75	0.572	0.686	0.563	0.633	0.496	0.633	0.730	0.377
80	0.581	0.689	0.573	0.640	0.508	0.640	0.729	0.373
85	0.589	0.691	0.582	0.646	0.519	0.646	0.727	0.369
90	0.596	0.693	0.590	0.652	0.529	0.652	0.726	0.366
95	0.603	0.695	0.597	0.657	0.539	0.657	0.724	0.364
100	0.609	0.697	0.604	0.661	0.548	0.661	0.723	0.362
100-year average (years 0 to 99)	0.459	0.593	0.446	0.513	0.382	0.513	0.643	0.417

Alternate Product Longevity (Decay Functions) Used in the Harvest Carbon Storage Calculator

The IPCC (2006) guidelines use the rate of decay of wood products, assuming "that the amount of woody material in use declines following a first-order decay," but note that "this is not the only assumption possible. Different possibilities include linear decay and more detailed approaches based on studies of the real use of these materials." IPCC (2019) explains that first-order decay—also called exponential decay—"means the annual loss from the stock of products is estimated as a constant fraction of the amount of the stock…. In the case of the 'products in use' pool, the outflow from the pool is calculated based on estimated half-life and associated decay rates of wood products from use assuming first-order decay rates." For countries that do not have their own estimates, IPCC's Tier 1 and 2 approaches provide default half-life values, and associated discard rates, for solid wood products and for paper products (IPCC 2019, table 12.2). Tier 3 methods with country-specific data may differ.

When accounting for carbon in wood products at the entity level, it is not possible to follow the change in stocks of wood products on hand and the rate of decay of products from all previous years, so focus should be on accounting for the lifetime of carbon held in current-year wood products—that is, the fate over time of the carbon held in the current-year output of wood products. The rate at which the discard of wood products and decay in landfills will release the product carbon as CO_2 is required for this estimation. Carbon that is released as CO_2 during the year of harvest must also be accounted for, and a method must be determined to account for the carbon that will be released in subsequent years.

Hoover et al. (2014) recommended methods to estimate carbon storage in wood products using the USDA Forest Service WOODCARB II model (Skog, 2008). The model uses calibrated estimates of product half-lives and limits the decay of wood and paper in landfills. It uses first-order dynamics for both the discard rates of products in use and the fraction of products in landfills that decay. It assumes that some fraction of wood products in landfills is permanent and never oxidized. In discussing uncertainty, Skog (2008) recognizes uncertainty in the fraction of solid wood and paper that is not subject to oxidation in a landfill and uncertainty in the shape of the decay distributions for both products in use and products that will decay in landfills, meaning they may be "different from first order decay" (p. 69).

Marland and Marland (2003) (see also Marland et al., 2010) state that the gamma distribution might be used to better describe the timing of the disposition of wood products over time. This alternate representation is conceptually no more difficult, although it is mathematically more complex than first-order decay. The gamma distribution may more accurately describe the rate at which wood products are removed from service and decay in landfills. In responding to Marland and Marland (2003), Pingoud and Wagner (2006) recognized that the gamma distribution could be closely fitted to many circumstances and that it would provide an elegant mathematical option for describing the real process. In fact, exponential decay (first-order decay) is a special case of the gamma function. The general gamma function has large flexibility and is based on two free parameters, noted as θ and κ in equation 5B-3. When $\kappa = 1$, the gamma distribution reduces to first-order, exponential decay. Another special case of the gamma function, characterized as chi-square, requires two parameters but carries a shape that is characteristic of many decay processes. Gamma is thus a widely used probability distribution function for which exponential and chi-square are special cases. In the chi-square case, κ describes the shape of the probability function and θ describes the scale (see Marland et al., 2010).

The gamma functions are represented in equation 5B-3 and illustrated in Figure 5-A-4 and figure 5-A-5. Whereas first-order decay assumes that the annual loss from the stock of products is a constant fraction of the amount of the stock, the chi-square function assumes that decay is a function of the time since production. First-order decay requires knowledge of only the half-life of the product, while the chi-square function requires estimates to represent both the time to maximum decay and a measure of the breadth of the distribution.

Equation 5B-3: Models of HWP Decay

$$\frac{dS}{dt} = \mathrm{J(t)} - \int_0^t P(t-\tau)J(\tau)d\tau$$

Where:

$$P(t,\kappa,\theta) = \frac{1}{\Gamma(\kappa)\theta^{\kappa}} t^{\kappa-1} e^{\frac{-t}{\theta}}$$

When κ = 1,

$$\frac{dS}{dt} = J(t) - \lambda S$$

First-order decay means the maximum amount of decay occurs in the first year, an unlikely circumstance for any product intended to serve a finite useful life. A chi-square probability distribution shows that the maximum rate of decays occurs at about the half-life. Figure 5B-1 shows the rate of decay for a first-order decay and for a chi-square decay for products with half-lives of 2.5, 12, 30, and 87.8 years, and figure 5B-1 illustrates the fraction remaining over time for the same probability descriptions of decay. The longer the service life of a class of products, the less likely that first-order decay can provide an accurate description. For long-lived products, the difference can be very important (Bates et al., 2017).

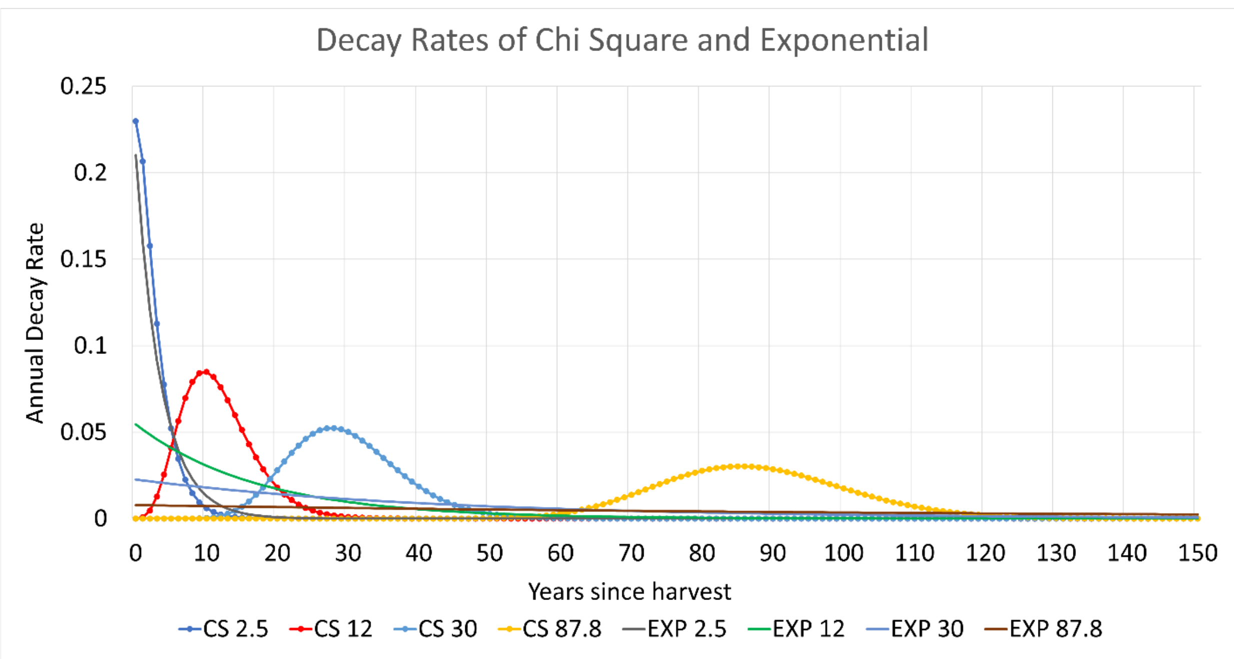


Figure 5B-1. Decay Rates for Chi-Square (CS) and Exponential (EXP) Probability Functions

Note that the exponential curves all start with their steepest decreases in earliest years and then flatten, whereas the chi-square curves peak as bell-shaped curves, with the highest rates of decrease stacked close to the actual half-lives. Chi-square curves have more delay, but more complete decay sooner than with the exponential curves.

Hazard function curves are a way to show how much of the original carbon remains through time. Figure 5B-2 shows the decimal decrease in remaining products in use when applying the exponential and gamma (chi-square) functions. These curves clearly show the differences between the two descriptions of "decay." Note that the curves sharing the same half-life cross very near their half-lives (e.g., CS-12 and E-12).

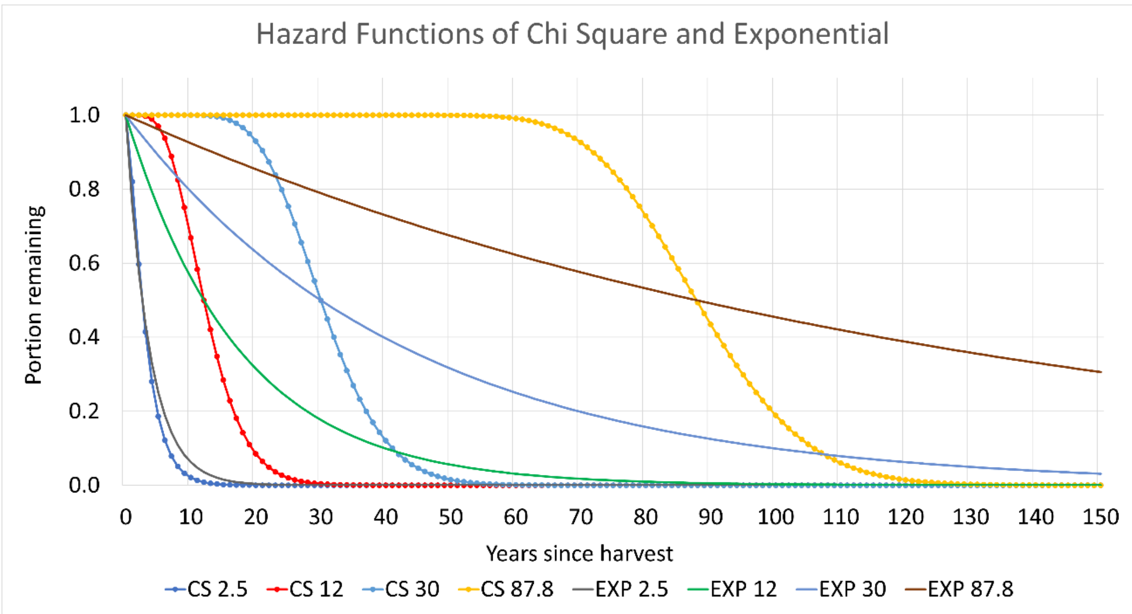


Figure 5B-2. Hazard Functions (Fraction Remaining Through Time) for Chi-Square (CS) and Exponential (E) Decay Curves

Because CO_2 emissions resulting from a given forest harvest that occurs during a discrete accounting year will occur over an extended number of years, a complete and accurate accounting of CO_2 emissions requires either a continued accounting and reporting of emissions in all subsequent years or an equitable protocol for anticipating all future emissions and accounting for the emissions during the initial accounting year that the forest was harvested. For accounting at the entity level, a few conventions have been widely adopted (e.g., those set by CARB, 2015).

End-of-Use Dispositions

Regardless of whether first-order or chi-square functions are used to portray the duration of product lives as products in use, once products are discarded, disposition ratios are relied on to shift products-in-use carbon into recycling, composting, burning with and without energy use, and landfills and dumps (SWDS).

Table 5B-7. Discard Percentages After Wood Products Have Completed Their Lives

Product Type	Disposition	2018 (%)
Paper	Burned	6
	Recycled	68
	Composted	0
	Landfills	26
	Dumps	0
Wood	Burned	16
	Recycled	17
	Composted	0
	Landfills	67
	Dumps	0

Source: Skog, 2020, personal communication, adapting U.S. EPA, 2020b. Skog (2008) summarized the understanding that some of the wood products in modern landfills "will stay there indefinitely with almost no decay." Recent U.S. EPA (2020a) estimates from 2018 indicate that 12 percent of solid wood carbon and 56 percent of paper carbon in landfills are subject to decay and indicated that solid wood and paper decaying in landfills had half-lives of 29 and 14.5 years, respectively (de Silva Alves et al., 2000; Freed and Mintz, 2003). Table 5B-9 summarizes the data used for calculations on carbon in landfills.

The combination of end-use lifespans, disposition, and decay rates in SWDS is also used to construct tables that show the percentage of wood remaining in products in use, the fraction remaining in SWDS, and (through subtracting from 1.0) the fraction emitted to the atmosphere by each year. These types of tables were originally constructed to derive a 100-year average for convenient representation of storage duration needed for financial compensation in carbon exchanges (e.g., Chicago, California). They will continue to be reported for the first 100 years, although carbon storage continues longer than 100 years for several primary products in several end uses (e.g., softwood lumber used in new home construction).

The harvest carbon calculator, described in section 5.2.2.1, uses these ratios and applies a set of assumptions about recycled material (a 2.5-year half-life for all paper products with unlimited recycling cycles). It then subjects 12 percent of solid wood and 56 percent of paper in landfills to decay.

Table 5B-8 shows the fractions of the carbon in wood products that is withheld from the atmosphere as a function of time for different products with different approximations of the half-life and for a chi-square version of the gamma function. The table also shows the average value over the commonly used 100 years (year 0 to year 99) and the value that would represent the average over 30 years, a time span that is typically meaningful for forest management decisions. Values out to 150 and 200 years are included to emphasize that the widely used 100-year average is a policy choice with no physical significance in terms of the system behavior. Table 5B-9 includes similar estimates of carbon remaining in SWDS.

Assumptions embedded in the results include a 5-percent discard when products are installed as end uses or used for the first time in year 1 (e.g., U.S EPA 2018b). Adhering to the disposition ratios in table 5B-8, 17 percent of the discarded material is recycled back into products in use. It is assumed that the half-lives, shown in table 5-8 (Skog, 2008), represent the year when half the wood installed in end-use products remains in these products.

Therefore, the Excel workbook applies a default chi-square distribution with these same half-lives to model alternative disposition rates into the future. Paper includes unlimited recycling (with a 0.68 rate with 0.7 efficiency), whereas solid wood products have a 0.17 rate with unlimited recycling. Paper, with a half-life in landfills of 14.5 years, is subject to faster landfill decay than solid wood, which has a landfill exponential decay with a half-life of 29 years. It is assumed that decay in landfills is exponential.

In general, it takes more time for products to transition to disposition than the fractions remaining in use generated by the exponential functions. However, the amount of carbon remaining at 100 years in solid wood products in the chi-square probabilities is roughly half of that from the exponential calculations. Whereas Hoover et al. (2014) chose to highlight the 100-year average results, this report presents the entire set of results in the calculator. However, the 100-year average can be a reasonable approximation of the avoided radiative forcing associated with carbon storage—a useful metric when 100-year GWPs are being used—so those results are also provided.

Table 5B-8. Total Carbon Fraction Remaining in End Uses: Chi-Square, Gamma Function

Time (Years Since Harvest)	Softwood Lumber	Hardwood Lumber	Softwood Plywood	Hardwood Plywood	Oriented Strand-board	NonStructural Panels	Other Industrial Products (Misc.)	Paper
0	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
1	0.950	0.948	0.950	0.950	0.950	0.950	0.950	0.943
2	0.948	0.935	0.949	0.950	0.950	0.950	0.950	0.864
3	0.945	0.910	0.946	0.949	0.950	0.949	0.948	0.787
4	0.939	0.875	0.942	0.946	0.949	0.946	0.941	0.716
5	0.931	0.835	0.936	0.941	0.947	0.941	0.927	0.651
6	0.921	0.794	0.929	0.932	0.943	0.932	0.900	0.591
7	0.908	0.753	0.919	0.919	0.938	0.919	0.862	0.537
8	0.893	0.713	0.908	0.902	0.931	0.902	0.812	0.487
9	0.876	0.676	0.896	0.882	0.924	0.882	0.753	0.442
10	0.859	0.642	0.883	0.861	0.915	0.861	0.688	0.402
11	0.841	0.610	0.870	0.839	0.906	0.839	0.621	0.365
12	0.824	0.582	0.857	0.817	0.897	0.817	0.555	0.331
13	0.807	0.557	0.845	0.796	0.888	0.796	0.491	0.301
14	0.791	0.534	0.833	0.776	0.879	0.776	0.433	0.273
15	0.776	0.514	0.821	0.757	0.871	0.757	0.380	0.248
16	0.762	0.496	0.809	0.739	0.863	0.739	0.333	0.225
17	0.748	0.480	0.797	0.722	0.855	0.722	0.292	0.204
18	0.734	0.465	0.785	0.706	0.847	0.706	0.257	0.185
19	0.720	0.450	0.773	0.689	0.839	0.689	0.226	0.168
20	0.706	0.436	0.759	0.673	0.831	0.673	0.200	0.153
21	0.692	0.422	0.746	0.656	0.822	0.656	0.177	0.139
22	0.678	0.408	0.731	0.638	0.814	0.638	0.157	0.126
23	0.663	0.393	0.716	0.619	0.805	0.619	0.139	0.114
24	0.649	0.378	0.701	0.599	0.797	0.599	0.124	0.104

Time (Years Since Harvest)	Softwood Lumber	Hardwood Lumber	Softwood Plywood	Hardwood Plywood	Oriented Strand-board	NonStructural Panels	Other Industrial Products (Misc.)	Paper
25	0.635	0.362	0.685	0.579	0.788	0.579	0.111	0.094
26	0.621	0.347	0.670	0.558	0.780	0.558	0.098	0.086
27	0.607	0.330	0.654	0.537	0.772	0.537	0.088	0.078
28	0.594	0.314	0.639	0.516	0.764	0.516	0.078	0.071
29	0.582	0.298	0.625	0.495	0.757	0.495	0.069	0.064
30	0.570	0.282	0.611	0.475	0.750	0.475	0.062	0.058
31	0.559	0.267	0.598	0.455	0.744	0.455	0.055	0.053
32	0.549	0.252	0.586	0.436	0.738	0.436	0.049	0.048
33	0.540	0.238	0.575	0.418	0.733	0.418	0.043	0.044
34	0.532	0.224	0.565	0.401	0.729	0.401	0.038	0.040
35	0.525	0.212	0.556	0.386	0.724	0.386	0.034	0.036
36	0.518	0.200	0.548	0.371	0.721	0.371	0.030	0.033
37	0.512	0.189	0.540	0.358	0.717	0.358	0.027	0.030
38	0.507	0.179	0.533	0.346	0.714	0.346	0.024	0.027
39	0.502	0.170	0.527	0.335	0.711	0.335	0.021	0.024
40	0.497	0.161	0.522	0.325	0.709	0.325	0.019	0.022
41	0.493	0.154	0.517	0.316	0.706	0.316	0.017	0.020
42	0.490	0.147	0.512	0.308	0.704	0.308	0.015	0.018
43	0.486	0.141	0.508	0.301	0.702	0.301	0.013	0.017
44	0.483	0.135	0.504	0.294	0.699	0.294	0.012	0.015
45	0.480	0.130	0.501	0.288	0.697	0.288	0.010	0.014
46	0.477	0.126	0.497	0.282	0.695	0.282	0.009	0.012
47	0.474	0.122	0.494	0.277	0.693	0.277	0.008	0.011
48	0.471	0.118	0.490	0.272	0.690	0.272	0.007	0.010
49	0.468	0.115	0.487	0.267	0.688	0.267	0.006	0.009
50	0.465	0.111	0.484	0.263	0.685	0.263	0.006	0.008
55	0.450	0.098	0.466	0.243	0.671	0.243	0.003	0.005
60	0.432	0.087	0.446	0.224	0.653	0.224	0.002	0.003
65	0.410	0.077	0.422	0.205	0.628	0.205	0.001	0.002
70	0.383	0.067	0.393	0.185	0.594	0.185	0.001	0.001
75	0.349	0.058	0.357	0.165	0.546	0.165	0.000	0.001
80	0.307	0.048	0.314	0.143	0.484	0.143	0.000	0.000
85	0.261	0.040	0.267	0.121	0.411	0.121	0.000	0.000
90	0.214	0.032	0.219	0.099	0.337	0.099	0.000	0.000
95	0.170	0.025	0.176	0.080	0.269	0.080	0.000	0.000
100	0.134	0.019	0.140	0.063	0.213	0.063	0.000	0.000
150	0.033	0.001	0.035	0.010	0.074	0.010	0.000	0.000
200	0.008	0.000	0.009	0.002	0.020	0.002	0.000	0.000

Time (Years Since Harvest)	Softwood Lumber	Hardwood Lumber	Softwood Plywood	Hardwood Plywood	Oriented Strand-board	NonStructural Panels	Other Industrial Products (Misc.)	Paper
30-year average	0.787	0.582	0.819	0.765	0.872	0.765	0.485	0.358
100-year average	0.503	0.240	0.523	0.381	0.659	0.381	0.151	0.114

Notes:

- It is assumed 12 percent of solid wood going to landfill decays and 88 percent does not (landfill permanent). Solid wood in landfills decays exponentially with a half-life of 29 years.
- It is assumed 56 percent of paper going to landfills decays and 44 percent does not (landfill permanent). Paper in landfills decays exponentially with a half-life of 14.5 years.
- Solve for κ in the chi-square distributions by setting the median equal to the half-life (equation 5B-3).
- Sixty-seven percent of disposed solid wood products go to landfills; 26 percent of disposed paper products go to landfills.
- Seventeen percent of disposed solid wood is recycled, including the 5-percent loss during installation in year 1.
- Sixty-eight percent of disposed paper products are recycled, with no installation loss at year 1.
- Landfill decay is assumed to be exponential.
- Hardwood plywood is pooled with nonstructural panels.
- Values indicate amounts at the beginning of the year rather than the middle or end of the year.
- This table assume a 5-percent loss of products at installation between year 0 and year 1.

Table 5B-9. Total Carbon Fraction Remaining in Landfills (SWDS): Chi-Square, Gamma Function

Time (Years Since Harvest)	Soft-wood Lumber	Hard-wood Lumber	Softwood Plywood	Hard-wood Plywood	Oriented Strand-board	Non-Structural Panels	Other Industrial Products (Misc.)	Paper
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.040	0.042	0.040	0.040	0.040	0.040	0.040	0.046
2	0.042	0.052	0.041	0.040	0.040	0.040	0.040	0.108
3	0.044	0.072	0.043	0.041	0.040	0.041	0.042	0.168
4	0.049	0.100	0.046	0.043	0.041	0.043	0.047	0.221
5	0.055	0.132	0.051	0.047	0.043	0.047	0.059	0.268
6	0.063	0.165	0.057	0.055	0.045	0.055	0.080	0.310
7	0.073	0.198	0.064	0.065	0.049	0.065	0.110	0.346
8	0.085	0.229	0.073	0.078	0.054	0.078	0.150	0.377
9	0.098	0.259	0.083	0.094	0.061	0.094	0.198	0.404
10	0.112	0.286	0.093	0.111	0.067	0.111	0.249	0.427
11	0.126	0.310	0.103	0.128	0.075	0.128	0.303	0.447
12	0.140	0.332	0.113	0.146	0.082	0.146	0.356	0.464
13	0.153	0.352	0.123	0.162	0.089	0.162	0.406	0.478
14	0.166	0.369	0.133	0.178	0.096	0.178	0.452	0.490
15	0.177	0.384	0.142	0.193	0.102	0.193	0.494	0.499

Time (Years Since Harvest)	Soft-wood Lumber	Hard-wood Lumber	Softwood Plywood	Hard-wood Plywood	Oriented Strand-board	Non-Structural Panels	Other Industrial Products (Misc.)	Paper
16	0.189	0.398	0.151	0.207	0.108	0.207	0.530	0.507
17	0.200	0.410	0.160	0.220	0.115	0.220	0.562	0.513
18	0.210	0.422	0.170	0.233	0.121	0.233	0.589	0.517
19	0.221	0.432	0.179	0.245	0.127	0.245	0.612	0.520
20	0.232	0.443	0.189	0.258	0.133	0.258	0.632	0.522
21	0.242	0.453	0.200	0.271	0.140	0.271	0.649	0.523
22	0.253	0.464	0.211	0.285	0.146	0.285	0.664	0.523
23	0.264	0.474	0.223	0.300	0.153	0.300	0.676	0.523
24	0.275	0.486	0.235	0.315	0.159	0.315	0.687	0.522
25	0.286	0.497	0.247	0.330	0.166	0.330	0.696	0.520
26	0.297	0.509	0.259	0.346	0.172	0.346	0.705	0.518
27	0.307	0.521	0.271	0.363	0.178	0.363	0.712	0.515
28	0.317	0.533	0.282	0.379	0.184	0.379	0.718	0.512
29	0.326	0.545	0.293	0.395	0.189	0.395	0.724	0.509
30	0.335	0.556	0.304	0.411	0.194	0.411	0.728	0.505
31	0.343	0.568	0.313	0.426	0.199	0.426	0.732	0.502
32	0.350	0.579	0.322	0.440	0.203	0.440	0.736	0.498
33	0.357	0.589	0.331	0.454	0.207	0.454	0.739	0.494
34	0.363	0.599	0.338	0.466	0.210	0.466	0.741	0.490
35	0.368	0.608	0.345	0.478	0.213	0.478	0.743	0.486
36	0.373	0.616	0.351	0.488	0.216	0.488	0.745	0.482
37	0.377	0.624	0.356	0.498	0.218	0.498	0.747	0.478
38	0.381	0.631	0.361	0.507	0.220	0.507	0.748	0.474
39	0.384	0.637	0.365	0.515	0.222	0.515	0.749	0.470
40	0.387	0.643	0.369	0.522	0.224	0.522	0.749	0.466
41	0.389	0.648	0.372	0.528	0.226	0.528	0.750	0.462
42	0.392	0.652	0.375	0.533	0.227	0.533	0.750	0.458
43	0.394	0.656	0.378	0.538	0.228	0.538	0.750	0.454
44	0.396	0.659	0.380	0.543	0.230	0.543	0.750	0.451
45	0.397	0.662	0.383	0.547	0.231	0.547	0.750	0.447
46	0.399	0.665	0.385	0.550	0.233	0.550	0.750	0.444
47	0.401	0.667	0.387	0.554	0.234	0.554	0.750	0.440
48	0.402	0.669	0.389	0.557	0.236	0.557	0.749	0.437
49	0.404	0.671	0.391	0.560	0.237	0.560	0.749	0.434
50	0.406	0.672	0.393	0.562	0.239	0.562	0.748	0.431
55	0.415	0.678	0.404	0.574	0.249	0.574	0.746	0.416
60	0.427	0.683	0.417	0.585	0.262	0.585	0.743	0.404
65	0.442	0.687	0.434	0.596	0.280	0.596	0.739	0.395
70	0.461	0.691	0.455	0.609	0.305	0.609	0.736	0.387

Time (Years Since Harvest)	Soft-wood Lumber	Hard-wood Lumber	Softwood Plywood	Hard-wood Plywood	Oriented Strand-board	Non-Structural Panels	Other Industrial Products (Misc.)	Paper
75	0.486	0.696	0.481	0.622	0.342	0.622	0.734	0.380
80	0.517	0.700	0.513	0.636	0.390	0.636	0.731	0.375
85	0.551	0.705	0.548	0.651	0.445	0.651	0.729	0.371
90	0.586	0.708	0.583	0.665	0.502	0.665	0.727	0.368
95	0.618	0.712	0.614	0.678	0.553	0.678	0.725	0.365
100	0.644	0.714	0.640	0.688	0.594	0.688	0.723	0.363
150	0.700	0.715	0.699	0.713	0.674	0.713	0.714	0.356
200	0.710	0.712	0.709	0.712	0.704	0.712	0.711	0.355
30-year average	0.168	0.329	0.143	0.186	0.100	0.186	0.406	0.410
100-year average	0.376	0.572	0.362	0.468	0.260	0.468	0.638	0.410

Notes:

- It is assumed 12 percent of solid wood going to landfill decays and 88 percent does not (landfill permanent). Solid wood in landfills decays exponentially with a half-life of 29 years.
- It is assumed 56 percent of paper going to landfills decays and 44 percent does not (landfill permanent). Paper in landfills decays exponentially with a half-life of 14.5 years. Solve for κ in the chi-square distributions by setting the median equal to the half-life (equation 5B-3).
- Sixty-seven percent of disposed solid wood products go to landfills; 26 percent of disposed paper products go to landfills.
- Seventeen percent of disposed solid wood is recycled, including the 5-percent loss during installation in year 1.
- Sixty-eight percent of disposed paper products are recycled, with no installation loss at year 1.
- Landfill decay is assumed to be exponential.
- Hardwood plywood is pooled with nonstructural panels.
- Values indicate amounts at the beginning of the year rather than the middle or end of the year.
- This table assume a 5-percent loss of products at installation between year 0 and year 1.

Table 5B-8 and table 5B-9 represent substantial development in this field and appear to more realistically represent the lifespans for durable wood products. There is ongoing discussion of whether paper products are better represented with an exponential function or a chi-square probability function. This discussion will be explored further in ongoing work, and options are provided to use in the harvest carbon calculator.

Table 5B-10 provides the converted GHG emissions (i.e., ton CO_2-eq emission/ton CO_2-eq) contained in the HWP. This version of the table using CO_2-eq for the product amounts (numerator) makes it easy to use results from the harvest carbon calculator in the substitution calculations.

Emission factors are also divided into the three life cycle stages as displayed in the table.

Table 5B-10. LCA Quantified GHG Emission Factors for Cradle-to-Gate Manufacturing of HWPs

Type	Cultivation and Harvest	Transportation	Manufacturing	Total
	Metric Tons CO_2-eq/Tons CO_2-eq Contained in the HWP Produced[a]			
Softwood lumber	0.015	0.012	0.061	0.088
Hardwood lumber	0.024	0.028	0.096	0.149
Plywood	0.077	0.012	0.173	0.263
Oriented strandboard	0.071	0.006	0.136	0.213
Non-structural panels	0.205	0.006	0.241	0.452
Other industrial products	0.055	0.037	0.056	0.148

[a] Values rounded to the thousandths place.

Calculator Demonstrations

The following example walks through the calculations performed by the growing stock calculator and the harvested wood carbon calculator, both embedded within the Excel workbook. Importantly, the models that underly some of the calculations in the demonstrations below include more decimals than are shown in the text, so slight discrepancies in results may be a function of rounding. As a brief navigation reminder:

- Read the information on the “Instructions and Context” tab before proceeding.
- Enter information on the “User Data Entry” tab.
- Depending on the forest management treatment and the region selected, real-time estimates for ecosystem carbon may or may not be available on the “User Data Entry” tab. The year-0 and year-100 results for HWP are part of the “Forest Management & HWP Results” tab.
- As stated in section 5.1.6, users can use default harvest volumes or provide their own to estimate the amount of ecosystem carbon that is taken off site as a result of harvest under the “Basic projection under fm, with harvest,” “Harvest,” or “Extended rotation” forest management activities available under the Level 1 approach. Consider that these two options are available when reviewing the calculator demonstrations:
    - **Advanced option.** Manually enter known harvest volumes or weights from logging/mill receipts or consultant reports, wood types (hardwood, softwood, unknown) and product types (sawlogs, pulpwood, fuelwood, unknown) as totals or per-acre values, as well as percentage of total growing stock harvested.
    - **Default data option.** Use default FIA data on regional growing stock volumes (cubic foot net volume per acre based on user-selected parameters around region/forest type group/stand age class/stand origin) for medium- and large-diameter stands to estimate harvest amounts.

In the following calculator examples, assume the user has the following criteria:

- The natural, spruce/fir, 1-square-mile forest stand is located in Maine and is about 21 to 40 years old. See figure 5-4 for a map of how the geographic regions are delineated.
- The scenario involves plans to harvest in 45 years.

- The expected harvest is softwood sawlogs; the user also plans to cut fuelwood in addition to industrial roundwood.

This criterion translates to the following selections on the “User Data Entry” tab.

- Basic inputs (blue section on the tab):
  - Type of forest management treatment to be applied: “Basic projection under fm, with harvest”
  - Area subject to management activity: 640 acres (1 square mile)
  - U.S. region: Northeast region
  - Forest type group: spruce/fir forest type group, natural stand origin, 21- to 40-year age class
- Silviculture and harvesting inputs (green and brown sections on the tab)
  - Number of years from now that you plan to harvest: 45
  - Percent of the area subject to management activity that will be harvested: 100 percent (the default)

Growing Stock Calculator

Default Data Option

- The user has limited knowledge on the harvest volume, but based on conversations with a local logger, the user expects to cut softwood sawlogs and plans to cut fuelwood in addition to industrial roundwood (sawlogs and pulpwood) for personal fuelwood use.
- This translates to the following Excel workbook data entry questions and example user selection on the “User Data Entry” tab:
  - Do you know what your harvest volume is? No
  - Main wood type of eventual products: Softwood
  - What is the main log type that will be produced from the trees removed? Sawlog
  - Should the tool apply default fuelwood values that are generated from sawlog and pulpwood production? Yes
- In the subsequent growing stock calculator analysis, the calculator:
  1. Begins with a FIADB CFNETVOL lookup for harvest volume. The age of the stand is the existing age stand plus the years until harvest. Since the midpoint of the current age class of 21–40 is 30, and the harvest is planned at 45 years, the age used by the lookup is 76 years, which falls in the 61–80 age class. The result is 15.28 CCF per acre, multiplied by all 640 acres, resulting in 9,780.9 CCF.
  2. Multiplies the result from step 1 by the softwood sawlog ratio of roundwood growing stock to volume that is removed as roundwood (0.991 from Smith et al., 2006, table 5). The result is 9,693 CCF.
  3. Multiplies the result from step 2 by the fraction of growing stock volume that is removed as roundwood, for softwood sawlogs in this region (0.948 from Smith et al., 2006, table 5) resulting in 9,189 CCF of softwood sawlogs.
  4. To expand back to the full growing stock and derive the fuelwood, the calculator divides the result from step 3 by the softwood sawlog ratio of roundwood to growing stock volume that is roundwood from Smith et al. (2006), table 5 (0.991), then multiplies by

the Northeast softwood sawlog ratio of fuelwood to growing stock volume that is roundwood (0.136): $\frac{9{,}189 \text{ CCF}}{0.991} \times 0.136 = 1{,}261 \text{ CCF}$.

So, in this example, the growing stock calculator estimates that the harvest in 45 years from 100 percent of the 640-acre stand will include 9,189 CCF softwood sawlogs and 1,261 CCF of softwood fuelwood. This information is then automatically moved into the harvest carbon calculator.

When the forest type group is unknown, the calculator uses an overall average of forest types by region. If the landowner does not know the forest type or wood type (i.e., softwood or hardwood) or the type of timber product (i.e., sawlog, pulpwood, or fuelwood), the calculator uses information from Smith et al. (2006) table 4 (fraction of growing stock volume that is softwood, fraction of growing stock volume that is sawtimber size) to allocate wood across a range of classes (softwood and hardwood, as well as sawlogs and pulpwood).

Advanced Option

This option may be preferred by users who have more advanced forestry operations and data or those who have had exchanges with an extension forester. It is only available for the "Basic projection under forest management (fm)" and "Basic projection under fm, with harvest" forest management activities in the Excel workbook.

This translates to the following Excel workbook data entry questions and example user selection:

- Do you know what your harvest volume is? Yes
- What is the amount you harvested or plan to harvest? (under product type 1): 7.5 MBF/acre
- What is the MAIN wood type of eventual products? Softwood
- What is the MAIN log type that will be produced from the trees removed? Sawlog
- Should the tool apply default fuelwood values that are generated from sawlog and pulpwood production? Yes

In the subsequent growing stock calculator analysis, the calculator:

1. Multiplies 640 acres $\times$ 7.5 MBF/acre = 4,800 MBF.
2. To expand back to the full growing stock and derive the fuelwood, the calculator divides the result from step 1 by the softwood sawlog ratio of roundwood to growing stock volume that is roundwood from Smith et al. (2006), table 4 (0.991).
3. Multiplies by the Northeast softwood sawlog ratio of fuelwood to growing stock volume that is roundwood (0.136): $\frac{4{,}800 \text{ MBF}}{0.991} \times 0.136 = 658.7 \text{ MBF}$.

So, in this example, the growing stock calculator estimates that the harvest in 45 years from 100 percent of the 640-acre stand will include 4,800 MBF softwood sawlogs and 658.7 MBF softwood fuelwood. This information is then automatically moved into the harvest carbon calculator (see the next example).

Harvest Carbon Calculator

In the advanced option example described above, the harvest amount is known. There are 4,800 MBF of Northeast spruce fir softwood sawlog volume and 658.7 MBF of Northeast spruce/fir fuelwood.

1. The harvest carbon calculator converts these inputs to an equivalent CCF, then chooses the highest value for each row. This prevents the user from double counting if they accidentally enter the same harvest in multiple units. This step uses one or two of four conversions depending on the provided units:
   - An MBF-to-CCF conversion, using a rate of 2.01 (based on a 4.97 ratio of board feet to cubic feet ratio, as well as the conversion factors of 1,000 board feet per MBF and 100 cubic feet per CCF).
   - A dry-tons-to-CCF conversion using the correct basic specific gravities, which allows conversion of green volumes to oven dry (zero moisture content) weight. In this case, the relevant specific gravity is softwood spruce fir's: 0.353, from Smith et al. (2006), table 4.
   - A green-tons-to-CCF conversion. This is the same as the dry-tons-to-CCF conversion, except that it also includes the dry log weight relative to wet log weight for softwoods (0.49), assuming an average moisture content of 106 percent for softwood (Forest Products Laboratory, 2010, table 4.1).
   - A cord-to-green-ton conversion of 2.15 tons per cord (all western, green tons without bark per cord; Winn et al., 2020, table 30).

   In this example, the CCF values are:

   $4{,}800 \text{ MBF} \times \frac{2.01 \text{ CCF}}{\text{MBF}} = 9{,}657.9 \text{ CCF}$ Northeast spruce fir softwood sawlog

   $658.7 \text{ MBF} \times \frac{2.01 \text{ CCF}}{\text{MBF}} = 1{,}325.4 \text{ CCF}$ Northeast spruce fir fuelwood

   The calculator then completes two sequential checks using two national biomass limits (Johnson, 2001) to ensure that no more than 66 percent of total site biomass is being harvested as industrial roundwood and no more than 78 percent of site biomass is being harvested as roundwood (sawlogs, pulpwood, and fuelwood). In both cases, if the amount being harvested is greater than the limit, the limit is divided by the percentage harvest to derive an adjustment factor, which is applied to all sawlogs and pulpwood for the first limit, followed by recalculation of fuelwood (when that is selected as harvested), and applied to sawlogs, pulpwood, and fuelwood for the second limit. These adjustments are made to the inputs for the harvest carbon calculator. Bark adjustments are captured in the harvest carbon calculator, working with the new limited amounts, and are linked to the potential substitution calculator.

2. The timber products are broken into primary products using table D6 from Smith et al. (2006) (table 5B-4). In this case, the calculator multiplies the sawlog volume by the following allocations. (There is no pulpwood in this example, but if there were, it would be allocated to a different set of ratios.)

   9,657.9 CCF × 0.391 (softwood lumber) = 3,776.3 CCF

   9,657.9 CCF × 0.000 (hardwood lumber) = 0 CCF

   9,657.9 CCF × 0.004 (softwood plywood) = 38.6 CCF

   9,657.9 CCF × 0.000 (hardwood plywood) = 0 CCF

   9,657.9 CCF × 0.000 (oriented strandboard) = 0 CCF

   9,657.9 CCF × 0.020 (nonstructural panel) = 193.2 CCF

   9,657.9 CCF × 0.083 (other industrial products) = 801.6 CCF

   9,657.9 CCF × 0.072 (wood pulp) = 695.4 CCF

9,657.9 CCF × 0.431 (fuel and other emissions) = 4,162.6 CCF

Note that these ratios should total 1.000, but they sum to 1.001 due to rounding.

3. The calculator then converts the CCFs from step 2 into carbon mass by multiplying each CCF by the correct basic specific gravities, which allows conversion of green volumes to oven dry (zero moisture content) weight:

$$\left(\frac{0.353 \times \frac{62.4\ \mathrm{lb}}{\mathrm{ft}^3}}{2{,}000\ \frac{\mathrm{lb}}{\mathrm{ton}}}\right) \times \frac{0.907185\ \text{metric ton}}{\text{ton}} \times \frac{100\ \mathrm{ft}^3}{\mathrm{CCF}} \times 0.5 = 0.4996\ \frac{\mathrm{Mg\ C}}{\mathrm{CCF}}$$

where 0.353 is the ratio of softwood spruce fir from Smith et al. (2006) table 4, and 0.5 is the carbon weight relative to dry wood.

3,776.2 CCF × 0.4996 (softwood lumber) = 1,886.5 Mg C

38.6 CCF × 0.4996 (softwood plywood) = 19.3 Mg C

193.2 CCF × 0.4996 (nonstructural panel) = 96.5 Mg C

801.6 CCF × 0.4996 (other industrial products) = 400.5 Mg C

695.4 CCF × 0.4996 (wood pulp) = 347.4 Mg C

therefore, = 2,750.1 Mg C (all products)

4,162.6 CCF × 0.4996 (fuel and other carbon) = 2,079.5 Mg C

It also calculates estimates from the fuelwood line:

1,325.4 CCF × 0.4996 (fuelwood) = 662.1 Mg C

The Fuel and other emissions are split into emissions with and without energy capture using Smith et al. (2006) table 7 with the tool weighting the capture ratios by timber product volumes. The results are converted to metric tons CO_2-eq and added to other emissions. Mg C results are shown in the emissions results in the harvest carbon calculator and they are converted into t CO_2-eq for the “Forest Mgmt & HWP Results” tab.

2,079.5 Mg × 0.5582 = 1,160.8 Mg Fuel and other emissions with energy capture

2,079.5 Mg × (1- 0.5582) = 918.7 Mg Fuel and other emissions without energy capture

4. The calculator multiplies the carbon mass for all products, fuel and other carbon, and fuelwood calculated in step 3 by table 5B-3’s ratios of carbon in bark to carbon in wood by region and timber product type (in this case, 0.182 for the sawlog-derived products and 0.185 for fuelwood (table does not provide fuelwood-specific ratios—pulpwood was selected)) to estimate the total bark carbon equivalent. To calculate the bark carbon emitted, the calculated bark carbon equivalent is multiplied by energy capture (0.5582) and without energy capture (1 – 0.5582), based coefficients and the formula provided in Smith et al. (2006) table D7 and its footnotes. Fuelwood and its bark are all assumed to be emitted with energy capture (1.0).

$(2{,}750.1 + 2{,}079.5\ \mathrm{Mg}) \times 0.182 \times 0.5582 = 490.7$ Mg equivalent sawlog bark carbon emissions with energy capture

$(2{,}750.1 + 2{,}079.5\ \mathrm{Mg}) \times 0.182 \times (1 - 0.5582) = 388.4$ Mg equivalent sawlog bark carbon emissions without energy capture

$662.1\ \mathrm{Mg} \times 0.185 \times 1.0 = 121.2$ Mg equivalent fuelwood bark carbon emissions with energy capture

Therefore,

$$\text{Total bark with energy capture} = (490.7 + 388.4 + 121.2 \text{ Mg C}) \times \frac{44 \text{ CO}_2\text{-eq}}{12 \text{ C}}$$
$$= 1{,}000.3 \text{ Mg or metric tons CO}_2\text{-eq}$$

5. The calculator multiplies the results in step 4 by the fractions remaining in end uses and fractions remaining in SWDS every year for the first 50 years and every 5 years from 55 to 100 years, as shown in table 5B-8 and table 5B-9. Note that all solid wood (not wood pulp/paper) products are reduced by 5 percent when end uses are installed between year 0 and year 1; this 5 percent is immediately disposed of at year 1. This next block of columns in this demonstration shows estimates of carbon from the sawlog line. For example, at year 10, 0.859 of softwood lumber and 0.883 of softwood plywood remain in end uses. Also at year 10, 0.112 of softwood lumber and 0.093 of softwood plywood remain stored in landfills. These remaining fractions are multiplied by the total amount produced in year 0 to obtain the total carbon amounts remaining in end uses and landfills. For example:

   Remaining in end uses at year 10:

   1,886.5 Mg C × 0859 (softwood lumber) = 1,620.5 Mg C

   19.3 Mg C × 0.883 (softwood plywood) = 17.0 Mg C

   Remaining in SWDS:

   1,886.5 Mg C × 0.112 (softwood lumber) = 211.7 Mg C

   19.3 Mg C × 0.093 (softwood plywood) = 1.8 Mg C

   To calculate the estimated carbon remaining in products in use and SWDS with conventional exponential functions, manually replace fractions remaining from table 5B-8 with those in table 5B-5 and fractions in table 5B-9 with those in table 5B-6.

   Remaining in end uses at year 10:

   1,886.5 Mg C × 0.700 (softwood lumber) = 1,319.7 Mg C

   19.3 Mg C × 0.722 (softwood plywood) = 13.9 Mg C

   Remaining in landfills (SWDS) at year 10:

   1,886.5 Mg C × 0.239 (softwood lumber) = 450.4Mg C

   19.3 Mg C × 0.221 (softwood plywood) = 4.3 Mg C

   In both cases, results across all primary product types are summed for each year and reported in the harvest carbon calculator, columns B, C and D as carbon stored in products in use, SWDS, and combined as Mg C or CO_2-eq.

   For example, using the chi-square lifespans, at year 10, products in use are estimated at 2,135.8 Mg C, SWDS at 472.5 Mg C, and combined HWPs stored at 2,608.3 Mg C. In the same row, in Columns F and G, note 95 percent of end-use carbon, but 47 percent of all log carbon (underbark) remained stored. During year 10, emissions with energy capture from the wood itself are estimated at 40 metric tons CO_2-eq, and emissions without energy capture are estimated at 29 metric tons CO_2-eq. By year 10, a total of 10,573 metric tons CO_2-eq is emitted (53 percent of total carbon in log removals (underbark)).

   Alternatively, in the results table on the “Harvest Carbon Calculator” tab in columns B, C and D, at row 80, for exponential end-use lifespans, at year 10, products in use are estimated at 1,703.2 Mg C, SWDS at 811.7 Mg C, and combined HWPs stored at 2,514.9 Mg C. This estimation is 91 percent of end-use carbon, but 46 percent of all log carbon (underbark). During year 10, emissions with energy capture are estimated at 437 metric tons CO_2-eq, and emissions without energy capture are estimated at 29 metric tons CO_2-eq. There is a total of

10,915 metric tons CO_2-eq emitted by year 10 (47 percent of total carbon in log removals (underbark)).

For this example, the ecosystem carbon stocks at year 45 are 175,980; subtracting that number from the year 0 stocks of 73,247 yields a cumulative ecosystem sequestration estimate of –102,733 tons CO_2-eq. On the "User Data Entry" tab, see the "Detailed Ecosystem Carbon Scenario Projection" part of the display to the right of the user selection for these values.

On the "Forest Mgmt & HWP Results" tab, the cumulative ecosystem sequestration value forms the beginning of the overall forest sector flux estimate. This tab's green section describes the resulting ecosystem pool:

A. Overall ecosystem carbon estimate before harvest: 175,980 metric tons CO_2-eq. This lines up with the year 45 total ecosystem carbon estimate from the "User Data Entry" tab.
B. CO_2-eq removed due to carbon stocks in sawlogs harvested: 17,709 metric tons CO_2-eq—that is, the amount of harvest reported in its CO_2-eq that was removed (recall in this example that 7.5 MBF/acre was removed) sawlogs.
C. CO_2-eq removed due to carbon stocks in pulpwood harvest: in this example, no pulpwood was removed.
D. But fuelwood was removed, as indicated by the 2,428 metric tons CO_2-eq on that row.
E. The result of the bark calculations indicates that 3,667 metric tons CO_2-eq was removed as bark and emitted from the ecosystem (in year 0, it is assumed).
F. Logging residue estimates from Smith et al. (2006), taken from Johnson (2001), were used to estimate the logging residue ecosystem emissions associated with the harvest: 5,289 metric tons CO_2-eq.
G. Remaining medium and large growing stock volume: zero, in this case, because extended harvest assumes 100 percent cut. (This number would show remaining wood under a harvest treatment with less than 100 percent removal.)
H. Remaining other aboveground carbon in the ecosystem after harvest: 146,887 metric tons CO_2-eq.

For the HWP section (the brown section on the tab) results are shown for year 0 (which in this case is 45 years from now, because that is when harvest is planned) and year 100, which corresponds to 145 years from now.

I. Amounts of carbon stored each of these years in harvested wood products in use: 10,084 and 959 metric tons CO_2-eq, respectively, for years 0 and 100.
J. Amounts stored in SWDS for each of the years: 0 and 6,265 metric tons CO_2-eq, respectively.
K. Emissions without energy capture: 3,369 and 4,718 metric tons CO_2-eq, respectively.
L. Emissions with energy capture: 6,684 and 8,194 metric tons CO_2-eq, respectively.

The total biogenic carbon stored from harvest (the sum of the storage subpools) is 10,084 metric tons CO_2-eq in use and 0 metric tons CO_2-eq in SWDS at year 0.

The final yellow cells on the tab show the total forest sector flux resulting from the management action in year 0; in other words, the net ecosystem exchange plus harvest minus change in HWP stock. This is the estimated stock change (flux) in forest sector carbon; it equals net ecosystem exchange (negative sequestration or zero sequestration) plus bark and logging residues emitted, plus harvested sawlogs, pulpwood, and fuelwood (annual stock change in harvested wood products in use and SWDS—year 0). The difference between total harvest and change in HWP equals HWP emissions with and without energy capture combined, so HWP emissions are captured indirectly in the following calculations.

Net ecosystem exchange is:

$$-102{,}733 + 3{,}667\ (\#\mathrm{E}) + 5{,}289 \text{ metric tons } \mathrm{CO_2}\text{-eq } (\#\mathrm{F}) = -93{,}777 \text{ metric tons } \mathrm{CO_2}\text{-eq}$$

Harvest is:

$$17{,}709\ (\#\mathrm{B}) + 0 \text{ metric tons } \mathrm{CO_2}\text{-eq } (\#\mathrm{C}) + 2{,}428 \text{ metric tons } \mathrm{CO_2}\text{-eq } (\#\mathrm{D}) = 20{,}136 \text{ metric tons } \mathrm{CO_2}\text{-eq}$$

Change in HWP stock is:

$$10{,}084\ (\#\mathrm{I}) + 0 \text{ metric tons } \mathrm{CO_2}\text{-eq } (\#\mathrm{J}) = 10{,}084 \text{ metric tons } \mathrm{CO_2}\text{-eq}$$

Therefore,

$$\text{Net Forest Sector Flux} = \text{Net Ecosystem Exchange} + \text{Harvest} - \text{Change in HWP Stock}$$

$$-93{,}777 + 20{,}136 - 10{,}084 \text{ metric tons } \mathrm{CO_2}\text{-eq} = -83{,}724 \text{ metric tons } \mathrm{CO_2}\text{-eq}$$

In other words, dependent on system boundaries across time this management action of waiting 45 years and then harvesting resulted in net forest sector flux of negative 83,724 metric tons CO_2-eq, meaning more carbon was sequestered than emitted under this scenario. No estimate is provided beyond the single harvest evaluation time (45 years from now or year 0), as there is not sufficient research to reliably estimate beyond that point. To toggle between the chi-square and exponential lifespan decay rates, use the down arrow that appears when cell B19 of the "Forest Mgmt & HWP Results" tab is selected. Switching between the options only affects the 100-year estimates in column D.

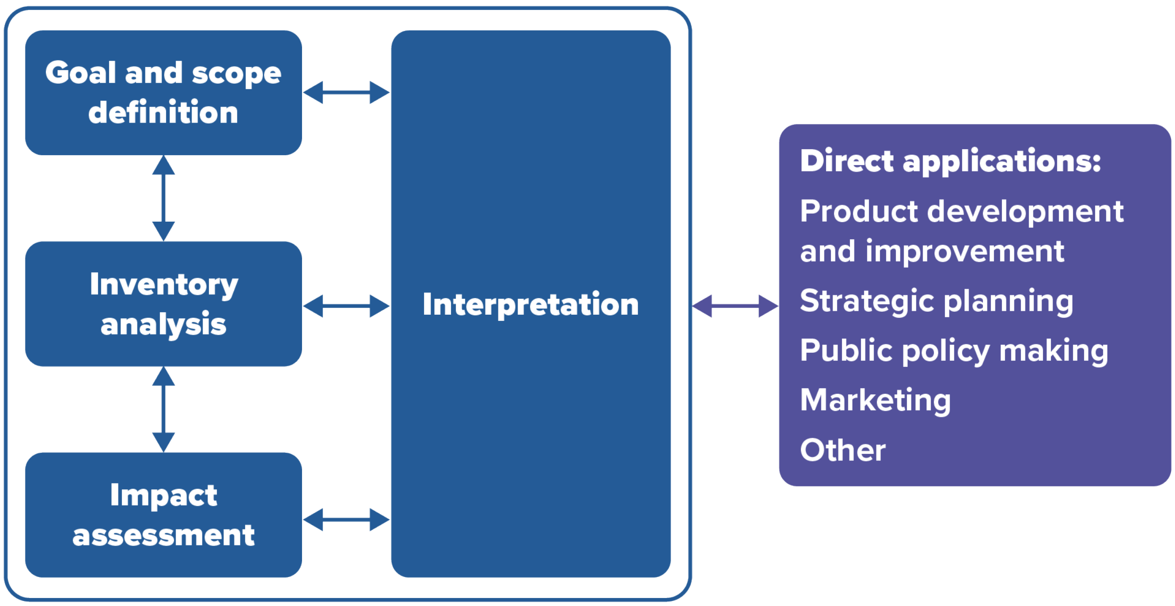
5-B.2.3 LCA Method Overview and Demonstration

Two related ISO standards provide globally acknowledged principles and a framework (ISO 14040:2006), and requirements and guidelines (ISO 14044:2006), for carrying out LCAs.

Following the standards, an LCA is performed in four major phases, which are interconnected to allow changes in one step based on new insights from another step:

1. **Goal and scope definition.** This phase defines the goal of the assessment, life cycle stages to be included, and quantitative functional unit of the product to be studied. The goal and scope depend on the intended use of study results. For example, life cycle stages would be different for (1) a cradle-to-gate study whose aim is to quantify the impacts of manufacturing a unit of softwood lumber and (2) a cradle-to-grave study that also covers the lumber's use and end-of-life treatment. Therefore, this phase of an LCA should be referenced to understand the methodological choices and intended application of the results.
2. **Inventory analysis.** This phase includes quantifying all environmentally significant inputs (material and energy flows) and outputs (environmental emissions) of the studied processes for the product system defined in the goal and scope phase. Analysis of these life cycle inventory flows provides preliminary data of the sources of GHG emissions.

3. **Impact assessment.** The life cycle inventory data are converted into potential environmental impacts with the help of characterization methods developed for different impact categories. For example, GHG emissions may be translated to global warming impacts based on an appraisal of GHG contributions to global warming.
4. **Interpretation.** In this phase, life cycle impact assessment results are interpreted with respect to the goal and scope definition and identified data gaps in order to provide recommendations for the intended audience.



Source: ISO 14040:2006.

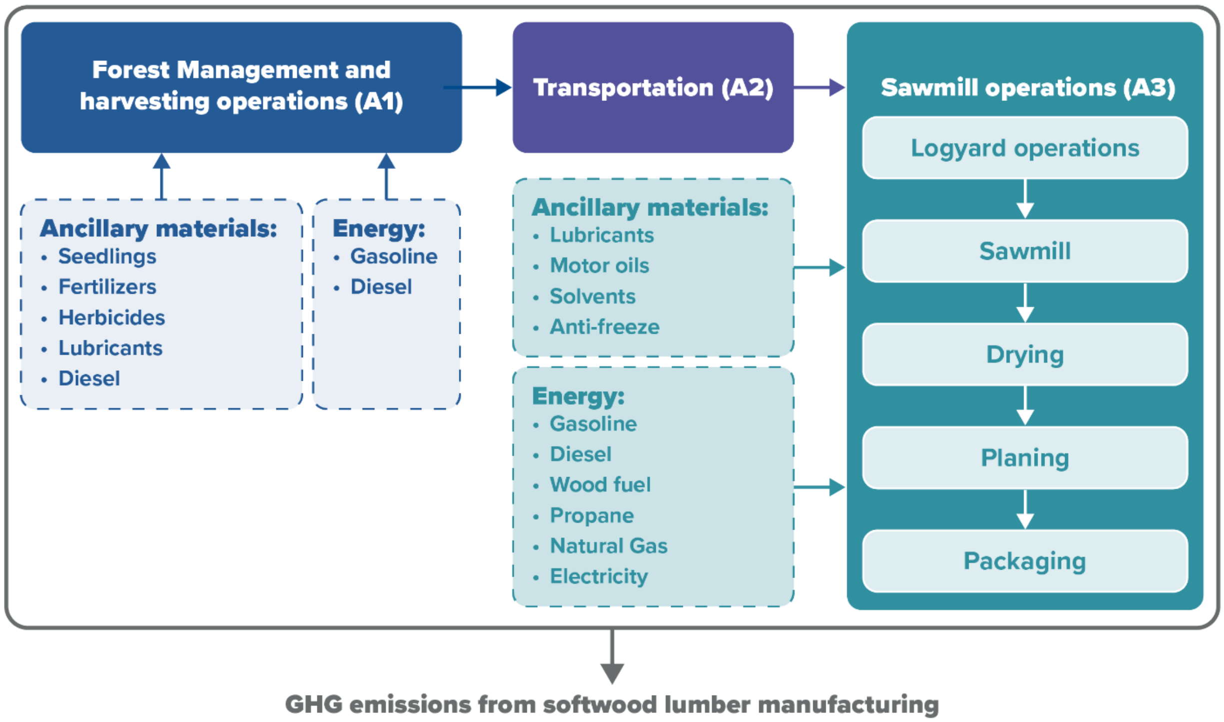
Figure 5B-3. Schematic of the LCA Phases and Their Interconnectedness

There are two types of LCA studies: attributional and consequential. An attributional LCA evaluates life-cycle environmental impacts associated with producing/using one functional unit of studied product or service. A consequential LCA evaluates change in environmental impacts due to a change in material inputs or service, comparing the outcomes under a baseline scenario with those under an alternate scenario. Consequential LCAs are typically used for policy changes: for example, evaluation of net GHG benefit of a policy that promotes wood use in the construction sector to replace high-carbon-emitting nonwood materials (e.g., steel and concrete).

Below is an example of an attributional LCA for an HWP: a study of softwood lumber by the Consortium for Research on Renewable Industrial Materials.

Example: Goal and Scope Definition

The Consortium's study sought to quantify the GHG emissions associated with 1 metric ton of softwood lumber manufactured in the U.S. Pacific Northwest, with a system boundary that spanned forest management and harvesting activities (cradle) to softwood lumber manufacturing and packaging (gate) for various end-use applications, including building construction. Key processes included within the identified system boundary are shown in figure 5B-4.



Source: Adapted from Puettmann (2020a).

Figure 5B-4. Cradle-to-Gate System Boundary for Softwood Lumber Manufacturing

Example: Inventory Analysis

The material and energy input–output data were collected for all the processes falling within the defined system boundary (figure 5B-4). Data from many softwood sawmills were collected, and weighted average values were estimated based on each mill's production capacity. The final aggregated inventory outputs from all the processes were converted to GHG emissions (including CO_2, CH_4, and N_2O) based on the functional unit of 1 metric ton of softwood lumber product.

Example: Impact Assessment

The impacts on environment from these GHG emissions were assessed by multiplying GHG inventory data for CO_2, CH_4, and N_2O by the pre-defined "characterization factors" referred to as GWPs, then added together, as shown in equation 5B-4 below:

Equation 5B-4: Impact Assessment

$$\sum_{i=CO_2,\, CH_4,\, N_2O} Inventory\ data\ (i) \times characterization\ factor\ (i) = Impact\ indicator\ results$$

The result, for 1 metric ton of softwood lumber product, averaged 0.161 metric ton of GHG emissions expressed as CO_2-eq.

Example: Interpretation

The impact assessment results obtained from the LCA study indicated that producing 1 metric ton of softwood lumber results in GHG emissions of 0.161 metric tons CO_2-eq from cradle to gate. The

LCA study also indicated that the sawmill operations were the largest contributor to these GHG emissions, followed by operations associated with management and harvesting activities, then transportation of roundwood to mills.

Potential Substitution Calculator

Estimates of the mass in metric tons carbon (from the harvest carbon calculator demonstration, above) are used for primary products as an input to estimate potential substitution effects. For example, 1,886.5 metric tons carbon of softwood lumber, produced from harvesting the 640 acres, with 7.5 MBF per acre, are first converted to tons CO_2-eq by multiplying by 3.67, then multiplied with the DF of 0.99 (described in section 5.2.2.1) to get 6,848 tons of total CO_2-eq reduction (substitution benefits) if substituting softwood lumber studs for steel studs in construction. Similar estimates are generated if any of the five other primary products from this land (hardwood lumber, plywood, oriented strandboard, nonstructural panels, and other industrial products) are produced. In this example, all primary products from harvesting the 640 acres, with 7.5 MBF per acre, could collectively reduce total GHG emissions by 11,384 metric tons CO_2-eq as construction substitution benefits.

For energy substitution potential, the calculator takes the emissions from fuelwood burned in year 0 and multiplies them by different numbers to show the potential displacement benefits of using this wood source instead of electricity, coal, oil, or gas. For example, total emissions from fuelwood burned in year 0 could displace 648 tons of fossil CO_2-eq emissions when wood energy replaces electricity, 1,651 tons of fossil CO_2-eq emissions when it replaces coal, 1,384 tons of fossil CO_2-eq emissions when it replaces heating oil, or 1,093 tons of fossil CO_2-eq emissions when it replaces natural gas. Emissions from "fuel and other" primary products, in year 0, are not explicitly shown in figure 5B-4. This is because most of those emissions are already folded into DFs for other primary products and are therefore mostly included in the product portion of the potential substitution calculator.

The calculator can also show the potential displacement from bark that was burned with energy capture. The 2,243 tons CO_2-eq emissions generated from burning bark, assuming the Smith et al. (2006) carbon content and use mill residue heating potential, could reduce the totals by 599, 1,525, 1,279, and 1,010 tons of fossil CO_2-eq emissions assuming it replaces electricity, coal, heating oil, or natural gas, respectively.

For purposes of demonstration, the wood product construction total (11,384 t CO_2-eq) and the most conservative energy (electricity) numbers (648 + 599 = 1,247 t CO_2-eq) are shown on the "Forest Management & HWP Results" tab as maximum substitution potential.

Products Produced from Harvest Calculato	Softwood Lumber Carbon (Mg)	Hardwood Lumber (Mg)	Softwood Plywood (Mg)	Hardwood Plywood (Mg)	OSB (Mg)	Non-structural panels (Mg)	Other industrial products (Mg)	Wood Pulp (Mg)	Total Processed Storage (Mg)	Fuelwood Emissions by this year (Mg)	Percent of HWP Emitted by this year
Amounts (Mg = Metric Tons)	1,886.500	-	19.299	-	-	96.496	400.459	347.386	2,750.140	662	50%

Bark biogenic emissions year of harvest with energy capture (Co2E)	Bark biogenic emissions year of harvest without energy capture (CO2E)	Percent of Bark emitted by this year
2,243	1,424	100%

Results - Potential Cradle to Gate Substitution Factors and Effects (C02E)

Displacement Factors											
Alternative Products Produced	Alternative Product: Steel Studs	Alternative Product: Doors	Alternative Product: Stutural Elements	Alternative Product: Stutural Elements	Alternative Product: Stutural Elements	Alternative Product: Non-Stuctural Elements	Alternative Product: Non-Stuctural Elements	Alternative Product: Non-Construction Uses	Total	Electricity	
Substitution factors (CO2e emissions avoided from wood substitution of non-wood fossil-based alternatives, estimated for cradle-to-gate life stages (Here negative implies reduced emissions potential)	-0.99	-2.29	-1.3	-1.3	-1.3	-1.6	-1.6	-1.2		-0.267	
Displacement Benefits (Here negative implies reduced emissions potential; this differs from how positive and negative are typically shown in LCA results, but it is consistent with our use of negative and positive elsewhere in our results.)	(6,848)	-	(92)	-	-	(566)	(2,349)	(1,528)	**(11,384)**	**(648)**	
										Anthracite Coal	
										-0.68	
										(1,651)	
										Heating Oil	
										-0.57	
										(1,384)	
										Natural Gas	
										-0.45	
										(1,093)	

Results Potential Bark Substitution

Electricity		
-0.267		
(599)		
Anthrocite Coal		
-0.68		
(1,525)		
Heating Oil		
-0.57		
(1,279)		
Natural Gas		
-0.45		
(1,010)		

Results - Emissions Outside the Biogenic HWP Carbon Storage or Flux

Products Produced from Harvest Calculato	Softwood Lumber Carbon (Mg)	Hardwood Lumber (Mg)	Softwood Plywood (Mg)	Hardwood Plywood (Mg)	OSB (Mg)	Non-structural panels (Mg)	Other industrial products (Mg)	Wood Pulp (Mg)	Total Processed Emissions without Wood Pulp
Metric Tons of Products Produced (t)	1,886.500	-	19.299	-	-	96.496	400.459	347.386	
Metric Tons CO2e of Products Produced (t	6,917.166	-	70.764	-	-	353.819	1,468.350	1,273.749	
LCA Quantified GHG Emissions from Cultivation and Harvest (t CO2eq)	0.015	0.024	0.077	0.077	0.071	0.205	0.055	No Data	
Results	104	-	5	-	-	73	81		**262**
LCA Quantified GHG Emissions from Transportation to the Mill (t CO2eq)	0.012	0.028	0.012	0.012	0.006	0.006	0.037	No Data	
Results	83	-	1	-	-	2	54		**140**
LCA Quantified GHG Emissions from Wood Processing (t CO2eq)	0.061	0.096	0.173	0.173	0.136	0.241	0.056	No Data	
Results	422	-	12	-	-	85	82		**602**
Total LCA Quantified GHG Emissions from Wood Cultivation, Harvest, Transportation and Processing (t CO2eq)	0.09	0.15	0.26	0.26	0.21	0.45	0.15	No Data	
Results	**609**	**-**	**19**	**-**	**-**	**160**	**217**		**1,004**

Figure 5B-5. Potential Substitution Calculator Demonstration

5-B.3 Wildfire and Prescribed Fire Methods

5-B.3.1 Rationale for Method

Given the escalating scale and severity of fire seasons, particularly across the U.S. West, the demand for information to estimate wildfire-related GHG emissions and inform fuel management actions is significant. However, quantifying avoided wildfire emissions from forest management activities such as fuel treatments requires highly complex models that consider the GHG-related implications of various forest management activities (including prescribed fire, fuel for harvest activities, and the long-term fate of HWPs); a probabilistic accounting for future fire likelihood and intensity; and a long-term model of the fate of burned carbon stocks, forest regrowth/regeneration potential, and subsequent disturbance risks.

For Level 1, the methodology offers a means to quantify an important but limited part of more indepth analysis of avoided wildfire emissions. Level 1 is a starting point for land managers seeking to understand the immediate impacts of low-severity prescribed burns and compare them to GHG impacts from higher severity fire events by compiling estimates of forest biomass combustion derived from simulations using FIA data as input to the FFE-FVS.

For Level 3, FFE-FVS was chosen as the model because it can simulate stand, fuel, and carbon dynamics over time while also being able to incorporate FIADB (Burrill et al., 2021) plot data within its modeling approach—that is, it is dynamically connected to contemporary forest resource information via FIA data. These are advantages over the FOFEM model prescribed in the 2014 guidelines (though FFE-FVS and FOFEM use many of the same internal algorithms for estimating and fuel consumption and emissions and a similar tree mortality approach).

FFE-FVS is a powerful predictive tool, offering a more advanced means to simulate fire impacts than simpler algorithms such as those in the *2006 IPCC Guidelines for National GHG Inventories* (IPCC, 2006) while also enabling simulation of various management approaches (e.g., clear-cut vs. timber stand improvement activities). In totality, this approach facilitates connections among national databases, modeling/simulation tools, and region/forest type configurations while acknowledging much work remains in refining approaches to estimating probabilities of future fire occurrence, forest management activities, and fuel dynamics under global change scenarios.

5-B.3.2 Technical Documentation

The forest types in this chapter correspond to the “forest type groups” described in the FIADB phase 2 user guide (Burrill et al., 2021, appendix D). These forest types are also listed explicitly in table 5B-11.

Table 5B-11. FIA Forest Type Group Names, Codes and Associated Forest Types

White/Red/Jack Pine Group	100
Jack pine	101
Red pine	102
Eastern white pine	103
Eastern white pine/eastern hemlock	104
Eastern hemlock	105
Spruce/Fir Group	**120**
Balsam fir	121
White spruce	122
Red spruce	123
Red spruce/balsam fir	124
Black spruce	125
Tamarack	126
Northern white-cedar	127
Longleaf/Slash Pine Group	**140**
Longleaf pine	141
Slash pine	142
Loblolly/Shortleaf Pine Group	**160**
Loblolly pine	161
Shortleaf pine	162
Virginia pine	163
Sand pine	164
Table Mountain pine	165
Pond pine	166
Pitch pine	167
Spruce pine	168

Oak/Pine Group	400
Eastern white pine/northern red oak/white ash	401
Eastern redcedar/hardwood	402
Longleaf pine/oak	403
Shortleaf pine/oak	404
Virginia pine/southern red oak	405
Loblolly pine/hardwood	406
Slash pine/hardwood	407
Other pine/hardwood	409
Oak/Hickory Group	**500**
Post oak/blackjack oak	501
Chestnut oak	502
White oak/red oak/hickory	503
White oak	504
Northern red oak	505
Yellow-poplar/white oak/northern red oak	506
Sassafras/persimmon	507
Sweetgum/yellow-poplar	508
Bur oak	509
Scarlet oak	510
Yellow-poplar	511
Black walnut	512
Black locust	513
Southern scrub oak	514
Chestnut oak/black oak/scarlet oak	515
Red maple/oak	519
Mixed upland hardwood	520

White/Red/Jack Pine Group	100
Pinyon/Juniper Group	**180**
Eastern redcedar	181
Rocky Mountain juniper	182
Western juniper	183
Juniper woodland	184
Pinyon/juniper woodland	185
Douglas-Fir Group	**200**
Douglas-fir	201
Port-Orford-cedar	202
Ponderosa Pine Group	**220**
Ponderosa pine	221
Incense-cedar	222
Jeffrey pine/Coulter pine/bigcone Douglas-fir	223
Sugar pine	224
Western White Pine Group	**240**
Western white pine	241
Fir/Spruce/Mountain Hemlock Group	**260**
White fir	261
Red fir	262
Noble fir	263
Pacific silver fir	264
Engelmann spruce	265
Engelman spruce/subalpine fir	266
Grand fir	267
Subalpine fir	268
Blue spruce	269
Mountain hemlock	270
Alaska yellow-cedar	271
Lodgepole pine group	**280**
Lodgepole pine	281
Hemlock/Sitka spruce group	**300**
Western hemlock	301
Western redcedar	304

Oak/Pine Group	400
Oak/Gum/Cypress Group	**600**
Swamp chestnut oak/cherrybark oak	601
Sweetgum/Nuttall oak/willow oak	602
Overcup oak/water hickory	605
Atlantic white-cedar	606
Baldcypress/water tupelo	607
Sweetbay/swamp tupelo/red maple	608
Elm/Ash/Cottonwood Group	**700**
Black ash/American elm/red maple	701
River birch/sycamore	702
Cottonwood	703
Willow	704
Sycamore/pecan/American elm	705
Sugarberry/hackberry/elm/green ash	706
Silver maple/American elm	707
Red maple/lowland	708
Cottonwood/willow	709
Oregon ash	722
Maple/Beech/Birch Group	**800**
Sugar maple/beech/yellow birch	801
Black cherry	802
Cherry/ash/yellow-poplar	803
Hard maple/basswood	805
Elm/ash/locust	807
Red maple/upland	809
Aspen/Birch Group	**900**
Aspen	901
Paper birch	902
Balsam poplar	904
Alder/maple group	910
Red alder	911
Bigleaf maple	912
Western Oak Group	**920**
Gray pine	921
California black oak	922
Oregon white oak	923

White/Red/Jack Pine Group	100
Sitka spruce	305
Western larch group	**320**
Western larch	321
Redwood group	**340**
Redwood	341
Giant sequoia	342
Other Western Softwoods Group	**360**
Knobcone pine	361
Southwest white pine	362
Bishop pine	363
Monterey pine	364
Foxtail pine/bristlecone pine	365
Limber pine	366
Whitebark pine	367
Miscellaneous western softwoods	368
California Mixed Conifer Group	**370**
California mixed conifer	371
Exotic Softwoods Group	**380**
Scotch pine	381
Australian pine	382
Other exotic softwoods	383
Norway spruce	384
Introduced larch	385

Oak/Pine Group	400
Blue oak	924
Deciduous oak woodland	925
Evergreen oak woodland	926
Coast live oak	931
Canyon live oak/interior live oak	932
Tanoak/Laurel Group	**940**
Tanoak	941
California laurel	942
Giant chinkapin	943
Other Western Hardwoods Group	**950**
Pacific madrone	951
Mesquite woodland	952
Cercocarpus woodland	953
Intermountain maple woodland	954
Miscellaneous western hardwoods woodland	955
Tropical Hardwoods Group	**980**
Sable palm	981
Mangrove	982
Other tropical	989
Exotic Hardwoods Group	**990**
Paulownia	991
Melaleuca	992
Eucalyptus	993
Other exotic hardwoods	995
Nonstocked	**999**

Results are presented in two tables: the FIRE table and the CARBON table (combined in the "Fire_Lookup" tab in the Excel workbook).

- The FIRE table provides immediate fire effects—biomass consumed, carbon emitted, GHG emissions, and postfire total stand carbon—which are binned into lookup tables based on FIA forest type group, geographic region, and fire severity. The lookup tables provide best-estimate (median) values and uncertainty appraisals (25 percent and 75 percent quantiles) of the metrics for each bin. An excerpt from the FIRE table for the Rocky Mountain South region is given in table 5B-13.
- The CARBON table provides prefire and immediate postfire carbon pool estimates. As with the FIRE table, the carbon pool estimates are aggregated into lookup tables based on FIA

forest type group, geographic region, and fire severity. Table 5B-14 provides an excerpt from the CARBON table for low-severity fire in the Rocky Mountain South Region.

For the conterminous United States, over 350,000 different combinations of region, forest type, and fire conditions were simulated. Carbon pool and GHG emission estimates for these simulations can be queried to produce reports using the Excel workbook.

GHG Pollutant Emission Factors, GWP, and CO_2-eq

Pollutant emission factors (PEFs) provide the mass of a pollutant emitted per unit mass of biomass carbon burned (g of pollutant per kg of carbon). Emissions of GHG *x*—denoted E_x—in units kg of *x*/hectare are calculated as:

Equation 5B-5: Pollutant Emission Factors

$$E_x = 0.001 \times PEF_x \times EC$$

Where:

E_x	=	emission rate of a given GHG (kg/ha)
0.001	=	PEF conversion factor (g/kg to kg/kg)
PEF_x	=	mass of a pollutant emitted per mass of biomass carbon burned (g pollutant/kg C)
EC	=	total carbon emitted (volatilized) by fire (kg C/hectare)

The CO_2 PEF includes carbon monoxide (CO), which accounts for up to 10 percent of volatilized carbon (Permar et al., 2021). CO resides in the atmosphere for a few months before being removed, primarily by gas phase oxidation to CO_2 (Khalil and Rasmussen, 1990; Cordero et al., 2019). Therefore, CO emissions are treated as CO_2 emissions and the PEF for CO_2 includes emitted CO. Note that, through atmospheric chemical reactions, CO indirectly affects the concentrations of other GHGs, and it has been proposed that CO emissions should have a GWP; see Myhre et al. (2013) for details. The PEFs for southern fires were used for the south central and southeastern regions, and the western/northern PEFs were used for all other regions. The PEFs for western and northern fires are based on airborne measurements of wildfires across the western United States. The PEFs may underestimate CH_4 emissions, since airborne measurement platforms may under-sample long-term smoldering of duff and coarse woody debris, which is characterized by a higher CH_4 PEF than other combustion processes (see Urbanski, 2014). The PEF for southern wildland fires synthesizes airborne and ground-based emission measurements from prescribed fires in southeastern forests (Urbanski, 2014). The CH_4 PEF will likely underestimate CH_4 emissions for fires involving significant peat/organic soil smoldering (Urbanski, 2014).

Table 5B-12. GHG PEFs and GWPs

GHG	PEF (g/kg C)[a]		GWP[b]
	Southern	Northern/Western	
CO_2	3,450	3,310	1
CH_4	4.6	13	28
N_2O	0.32	0.32	265
CO_2-eq	3,660	3,730	—

[a] Myhre et al. (2013).

[b] IPCC Fifth Assessment Report (IPCC, 2013).

Table 5B-13. Data Fields of the FIRE Table: Estimated Carbon and GHG (CO_2, CH_4, N_2O) Emissions, Biomass Consumed, and Postfire Total Stand Carbon

Column	Variable Name	Units	Description
1	region	None	Geographic region code
2	forgrp	None	FIA forest type group code
3	fire_sev	None	Fire severity code
4	Total_Stand_Carbon_50%	Mg carbon per hectare	Best estimate (median) of total stand carbon postfire
5	Total_Stand_Carbon_25%	Mg carbon per hectare	Lower bound estimate (25th percentile) of total stand carbon postfire
6	Total_Stand_Carbon_75%	Mg carbon per hectare	Upper bound estimate (75th percentile) of total stand carbon postfire
7	Carbon_Released_From_Fire_50%	Mg carbon per hectare	Best estimate (median) of carbon emitted by fire
8	Carbon_Released_From_Fire_25%	Mg carbon per hectare	Lower bound estimate (25th percentile) of carbon emitted by fire
9	Carbon_Released_From_Fire_75%	Mg carbon per hectare	Upper bound estimate (75th percentile) of carbon emitted by fire
10	Total_Consumption_50%	Mg biomass per hectare	Best estimate (median) of biomass consumed by fire
11	Total_Consumption_25%	Mg biomass per hectare	Lower bound estimate (25th percentile) of biomass consumed by fire
12	Total_Consumption_75%	Mg biomass per hectare	Upper bound estimate (75th percentile) of biomass consumed by fire
13	ECO_2_50%	Mg CO_2 per hectare	Best estimate (median) of CO_2 emitted by fire
14	ECO_2_25%	Mg CO_2 per hectare	Lower bound estimate (25th percentile) of CO_2 emitted by fire
15	ECO_2_75%	Mg CO_2 per hectare	Upper bound estimate (75th percentile) of CO_2 emitted by fire
16	ECH_4_50%	Mg equivalent CO_2 per hectare	Best estimate (median) of CH_4 emitted by fire
17	ECH_4_25%	Mg equivalent CO_2 per hectare	Lower bound estimate (25th percentile) of CH_4 emitted by fire
18	ECH_4_75%	Mg equivalent CO_2 per hectare	Upper bound estimate (75th percentile) of CH_4 emitted by fire
19	EN_2O_50%	Mg equivalent CO_2 per hectare	Best estimate (median) of N_2O emitted by fire
20	EN_2O_25%	Mg equivalent CO_2 per hectare	Lower bound estimate (25th percentile) of N_2O emitted by fire
21	EN_2O_75%	Mg equivalent CO_2 per hectare	Upper bound estimate (75th percentile) of N_2O emitted by fire
22	ECO_2equiv_50%	Mg equivalent CO_2 per hectare	Best estimate (median) of total GHG emitted by fire
23	ECO_2equiv_25%	Mg equivalent CO_2 per hectare	Lower bound estimate (25th percentile) of total GHG emitted by fire
24	ECO_2equiv_75%	Mg equivalent CO_2 per hectare	Upper bound estimate (75th percentile) of total GHG emitted by fire

Table 5B-14. Data Fields of the CARBON Table: Estimated Prefire, Postfire, and Change in Carbon Pools (Mg C/ha)

Column	Variable Name	Units	Description
1	region	None	Geographic region code
2	forgrp	None	FIA forest type group code
3	fire_sev	None	Fire severity code
4	status	None	Prefire, postfire, or change
5	Aboveground_Total_Live_50%	Mg carbon per hectare	Best estimate (median) of carbon in total aboveground live biomass
6	Aboveground_Total_Live_25%	Mg carbon per hectare	Lower bound estimate (25th percentile) of carbon in total aboveground live biomass
7	Aboveground_Total_Live_75%	Mg carbon per hectare	Upper bound estimate (75th percentile) of carbon in total aboveground live biomass
8	Belowground_Live_50%	Mg carbon per hectare	Best estimate (median) of carbon in belowground live biomass
9	Belowground_Live_25%	Mg carbon per hectare	Lower bound estimate (25th percentile) of carbon in belowground live biomass
10	Belowground_Live_75%	Mg carbon per hectare	Upper bound estimate (75th percentile) of carbon in belowground live biomass
11	Belowground_Dead_50%	Mg carbon per hectare	Best estimate (median) of carbon in belowground dead biomass
12	Belowground_Dead_25%	Mg carbon per hectare	Lower bound estimate (25th percentile) of carbon in belowground dead biomass
13	Belowground_Dead_75%	Mg carbon per hectare	Upper bound estimate (75th percentile) of carbon in belowground dead biomass
14	Standing_Dead_50%	Mg carbon per hectare	Best estimate (median) of carbon in total standing dead biomass
15	Standing_Dead_25%	Mg carbon per hectare	Lower bound estimate (25th percentile) of carbon in standing dead biomass
16	Standing_Dead_75%	Mg carbon per hectare	Upper bound estimate (75th percentile) of carbon in standing dead biomass
17	Forest_Down_Dead_Wood_50%	Mg carbon per hectare	Best estimate (median) of carbon in DDW
18	Forest_Down_Dead_Wood_25%	Mg carbon per hectare	Lower bound estimate (25th percentile) of carbon in DDW
19	Forest_Down_Dead_Wood_75%	Mg carbon per hectare	Upper bound estimate (75th percentile) of carbon in DDW
20	Forest_Floor_50%	Mg carbon per hectare	Best estimate (median) of carbon in forest floor
21	Forest_Floor_25%	Mg carbon per hectare	Lower bound estimate (25th percentile) of carbon in forest floor
22	Forest_Floor_75%	Mg carbon per hectare	Upper bound estimate (75th percentile) of carbon in forest floor
23	Forest_Shrub_Herb_50%	Mg carbon per hectare	Best estimate (median) of carbon in shrub and herb
24	Forest_Shrub_Herb_25%	Mg carbon per hectare	Lower bound estimate (25th percentile) of carbon in shrub and herb

Column	Variable Name	Units	Description
25	Forest_Shrub_Herb_75%	Mg carbon per hectare	Upper bound estimate (75th percentile) of carbon in shrub and herb
26	Total_Stand_Carbon_50%	Mg carbon per hectare	Best estimate (median) of total stand carbon
27	Total_Stand_Carbon_25%	Mg carbon per hectare	Lower bound estimate (25th percentile) of total stand carbon
28	Total_Stand_Carbon_75%	Mg carbon per hectare	Upper bound estimate (75th percentile) of total stand carbon

5-B.4 Urban Forest Management

5-B.4.1 Rationale for Method

The rationale for the i-Tree methods is grounded in i-Tree's dynamic development, expansion, and refinement. Since its introduction in 2006, the i-Tree program (including methodologies, databases, and software) has focused on urban ecosystem service evaluation and urban forest management guidance by providing the environmental benefits and services of urban and community trees and forests, including carbon storage and sequestration. Since its origin, i-Tree continues to be updated, expanded, and refined with new science and data: the current version is a consistent, yet substantial improvement and update over the approach recommended in the 2014 guidelines. This continued development in the i-Tree program will allow users to get the most up-to-date science and improved carbon accounting, as well as many other tree and forest benefit values, now and into the future.

Appendix 5-C: Summary of Research Gaps for Forestry Systems

5-C.1 General Interactions

There may be interactions between biological and physical processes that are affected by forest management treatments or natural disturbances, such as the albedo effect, evaporation, and turbulence (Bright et al., 2017). For example, the Earth's albedo is the fraction of sunlight and energy it reflects back into the atmosphere. Snow, with its light color, has high albedo; dark land cover absorbs sunlight energy and has a low albedo effect. In the context of forest management and its effects on climate change, trees (depending on species and density) may have a low albedo, contributing to a warmer surface temperature. This suggests that albedo changes due to tree planting and forest management could counteract anticipated climate benefits in the absence of other biophysical conditions. This is an emerging field of study, involving complex relationships that depend on many factors and biophysical interactions are not included in these methods. Beyond the estimation of climatic impacts, the calculation of ecosystem co-benefits (e.g., water, wildlife habitat, cultural values) is beyond the objective of these guidelines, though there are recognized interactions between these ecosystem functions and GHG fluxes (e.g., impacts of belowground biodiversity on tree growth (Prescott and Grayston, 2023)).

5-C.2 Silviculture and Improved Forest Management

The intersection of silviculture (i.e., the intentional manipulation of ecosystem carbon across varying combinations of tree species and structures), the complexities associated with forest carbon estimation (e.g., for soils and/or dead wood), and uncertain future climates suggest a litany of opportunities to increase the accuracy and associated applied knowledge of climate adaptation/mitigation and forest management efforts. Although a full examination of this topic is beyond the purview of this chapter, some of the largest research opportunities are in stand management projection (i.e., growth and yield modeling) and development of adaptive silviculture for climate change applications with a focus on carbon implications.

To refine estimates of emissions at harvest, further studies and data are needed to characterize transfers of live to dead biomass carbon and soil carbon pools, emission rates, and what proportion of the total biomass ultimately enters the HWP pool. More data would enable a more complete and connected quantification of the impacts of forest management from ecosystems to products in use to SWDS. In addition, the variety of site preparation techniques commonly employed during even-aged silvicultural systems (including root-raking, roller drum chopping, chemical applications, and/or fertilization) should be quantified in entity-scale guidelines for more complete assessments of GHG flux.

Finally, a more comprehensive inclusion of the variety of silvicultural systems from uneven-aged to even-aged is a necessity for further emission estimates refinements, especially as the full breadth of such management approaches may be needed for society to adapt to future climate change. Perhaps objective classification of management techniques and associated identification across United States forest ecosystems, coupled with spatially explicit estimates of forest change, would empower adaptation, improve market opportunities, and reduce uncertainty in forest carbon projections for policymakers.

5-C.3 Harvested Wood Products

5-C.3.1 Data Gaps

In a number of cases, this chapter applies data that have not been updated for long periods (e.g., 1998 data to allocate harvests to primary wood products, 2009 data to allocate primary products to end uses). Landfill assumptions for paper in table 5B-13 are based on Freed and Mintz (2003), cited in Smith et al. (2006) notes. Landfill assumptions for solid wood products are based on U.S. EPA WARM, indicating 88 percent of carbon lumber (used for solid wood) is stored permanently; this is a lumber figure only.

The DFs for emerging HWP use (e.g., mass timber products, wood energy products) need to be defined to quantify impactful GHG reduction benefits over time. More LCA studies and national or regional timber product output data, especially for these emerging HWPs, will be needed. Additionally, the long-term fates, product yield, end uses, and end-of-life fates for HWP are needed. HWP and associated industries/uses may need to be considered as an ecosystem unto itself: perhaps comprehensive entity-scale guidelines can only be realized by equally matching the sophistication of ecosystem carbon assessment with the tightly coupled HWP "ecosystem."

5-C.3.2 Research Gaps

Decay Function Evaluation

This chapter provides both the conventional (i.e., exponential) and alternative chi-square functions to represent the lifespans for long-lived products and their decay in landfills in the production approach. However, refined data in this topic area would be very helpful as a tool to mitigate climate change, especially as carbon markets—which normally rely on projections of carbon storage—continue to grow.

Substitution Benefits Evaluation

Underlying differences in wood and nonwood products should be characterized with more data on manufacturing technologies and more precision in choosing equivalent alternatives. The LCA studies for both wood and nonwood products, used to assess the substitution factors, have inherent heterogeneity and uncertainties, and are not expected to remain constant (Harmon, 2019). The Level 2 and 3 updates in substitution factors aim to reduce this variability by collecting more data on GHG emissions. The choice of allocation method for distributing GHG emissions between main products and coproducts and the inclusion of life cycle stages in the system boundary would be critical (Keith et al., 2015). These choices would greatly influence the estimated DFs and subsequent interpretations of the substitution benefits.

Because uncertainties exist in the currently reported HWPs' DFs, more research is needed to define individualized DFs for every possible HWP substitution; then, more accurate substitution benefits can be quantified. This need includes bark substitution factors. Emerging mass timber products, such as cross-laminated timber, have been adopted into new building construction and remodeling. For nonresidential and mid- to high-rise building construction, the precise DFs for cross-laminated timber and other mass timber products will be critical to quantify the substitution impacts in the building sector.

The biomass energy substitution benefits could be enhanced if forest residues, thinned trees, or other fire-reduction-induced biomass were collected for energy substitutions. Research is needed to quantify the impacts with the LCA—in particular, to include benefits and costs in other realms (such as wildlife habitat and nutrient cycling)—to maximize potential GHG displacement benefits from using these sources of woody biomass.

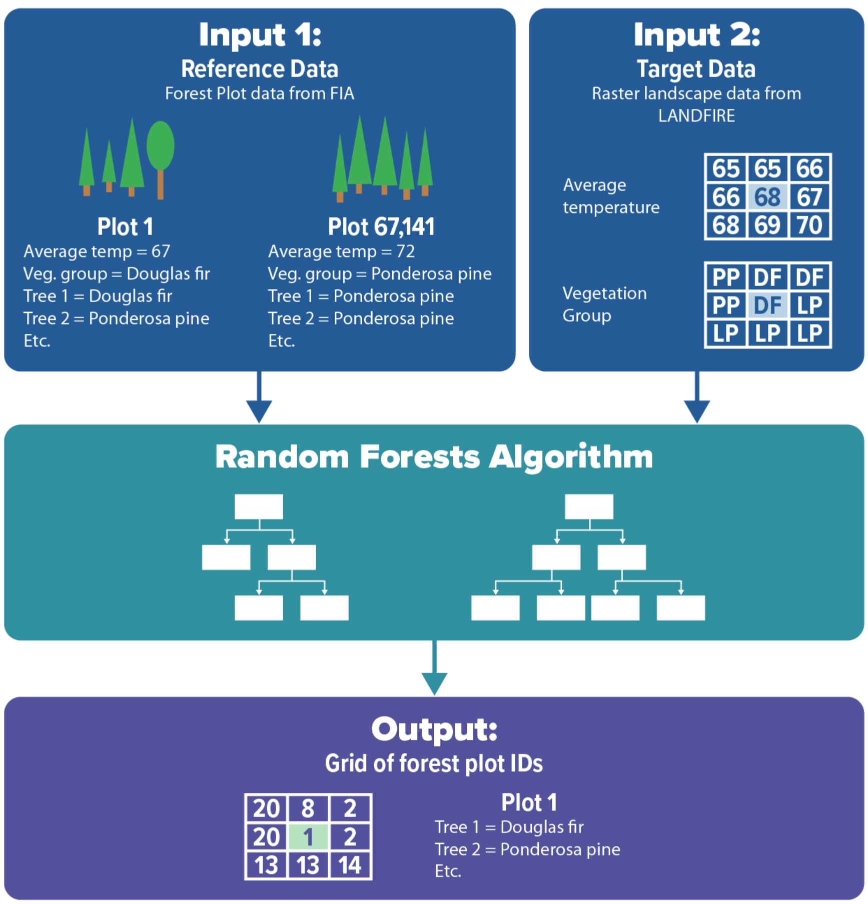
5-C.4 Wildfire and Prescribed Fire Methods

The following subsections outline known future improvements, due to current research and understanding gaps, to the methods provided in this chapter.

5-C.4.1 Spatially Explicit GHG Emissions

The current methodology provides estimates of GHG emissions and carbon pool fluxes attributable to wildland fire, aggregated by region and forest type. Improved estimates could be provided through a spatially explicit product based on TreeMap (Riley et al., 2021), a continental-U.S.-wide gridded dataset linked to FIA forest plots. TreeMap may be a solution for users who need spatially explicit estimates of carbon pool and GHG fluxes and have access to GIS analyst skills.

Figure 5C-1 shows a potential implementation of a TreeMap-based GHG emission estimation method. In the figure, the TreeMap dataset (Riley et al., 2021) assigns an FIA plot to each 30-by-30-meter pixel based on a suite of predictor variables including topography, vegetation, biophysical conditions, and disturbance.



Source: Riley et al. (2021).

Figure 5C-1. Workflow for Generating Maps Using TreeMap Data

Each FIA plot identifier is linked to a list of trees and their characteristics, including species, dbh, and height, and many plots have information on DDW as well. Each color in the map corresponds to a unique plot. Cadastral boundaries can be overlaid with the TreeMap to extract information about trees and DDW for a given parcel; from these characteristics, carbon can be estimated in FFE-FVS.

5-C.4.2 Postfire Carbon Trajectories

Another major improvement to the methodology presented in this section would be the addition of postfire (and no-fire) carbon pool time-series. FVS could be used to simulate postfire forest regeneration and growth for 50–100 years to provide long-term carbon trajectories for the recovering forest (Raymond et al., 2015). FVS simulations run under a no-fire scenario would provide a baseline carbon trajectory that, when compared with various fire scenarios, would provide estimates of indirect carbon emissions. The generation of long-term forest trajectories with FVS does not represent a major technical undertaking relative to the methods used to develop the immediate fire-induced GHG emissions presented in this section. However, uncertainties in the reliability of postfire FVS forest simulations, future site disturbances, and climate change make the interpretation and use of such trajectories very challenging.

Postfire forest regeneration and growth simulated by FVS is highly uncertain, in large part due to gaps in current scientific understanding of these processes, as well as uncertainty in factors driving regeneration, such as timing and amount of postfire precipitation and drought. The literature varies in the response of carbon trajectories postfire, especially in lower-severity prescribed fires and other fuel reduction methods. Many studies show a carbon benefit a few decades after a prescribed fire (Hurteau et al., 2016; Liang et al., 2018; Loudermilk et al., 2016; McCauley et al., 2019), but others show it may take longer to recover the carbon lost from even low-severity fires (Ager et al., 2010; Campbell et al., 2012; Spies et al., 2017). This is one of the largest sources of uncertainty on the overall impact of wildfire on carbon storage, because whether carbon sequestration is suppressed for 1 year or more than 10 years has a large effect on long-term carbon storage.

Other challenges in modeling postfire carbon trajectories include forecasting the timing and severity of future fires, which will be affected by climate change. Trajectories in future climate are themselves uncertain and will also have effects on forest structure, including regeneration failure in some areas, as well as increased susceptibility to insects and disease due to drought stress. Finally, the assessment of GHG emissions from pile burning and estimation of future avoided wildfire emissions (i.e., catastrophic emissions) warrants future research to empower decision making in the context of managing fire vs. implicitly accepting emissions from future wildfires.

5-C.5 Urban Forest Management and/or Trees Outside Forests

Approaches to quantify carbon storage and annual sequestration from urban forest management can also be improved with more field data collection in urban areas, and with model and method improvements related to carbon estimation. Support of ongoing and initiation of new research focused on improving and updating the allometric equations in i-Tree is warranted. More research is needed on the applicability of forest-derived equations to urban trees. In addition, more urban tree growth data are needed to better understand regional variability of urban tree growth under differing site conditions (e.g., tree competition) for better annual sequestration estimates. Average regional growth estimates are used based on limited measured urban tree growth data standardized to length of growing season and crown competition.

Estimates of maintenance emissions and altered building energy use effects need further evaluation and refinement to advance more complete carbon accounting while also improving the scientific community's understanding of relationships between trees and building energy usage. Research on urban forest management activities should also include more carbon and environmental benefit analysis of urban biomass utilization and waste, aligning with the methods developed for the section on HWPs, LCA, and substitution (section 5.2.2).

For both photo interpretation and online geospatial database methods, supporting both ongoing and new high-resolution aerial imagery and land cover projects throughout the country will improve those methods. In addition, further development of i-Tree tools is needed to allow a finer-scale user selection (smaller than census block groups) for carbon accounting.

Finally, between urban and rural forests there are a spectrum of trees across the landscape for which associated GHG benefits can be calculated but are not included in this version. For example, the use of trees in agroforestry systems, silvopasture, or even nut/fruit tree orchards is somewhere between the land uses of forests and agricultural systems. It should not be overlooked; analytical procedures such as small area estimation (Prisley et al., 2021), as well as the use of high-resolution remotely sensed information, may advance understanding in this area.

5-C.6 Uncertainty Data Gaps

While there are some known default values (see appendix 5-B), quantifying uncertainty as an implicit, explicit-model, or explicit-measurement-based method, as discussed in chapter 8, requires more information than was available for this version of the report. To encourage transparency, USDA noted this gap within the chapter and hopes to prioritize this improvement in the next version of the report.

Broadly, there is often uncertainty associated with estimates of forest carbon, such that even at large scales (e.g., State-level), the power to detect statistically significant changes in forest carbon stocks is limited to major disturbances (Westfall et al., 2013). Compounding the sampling error often associated with forest inventories, there is measurement and model error that may not be known. Users of any inventories, lookup tables, or models should remain aware of these potential errors as they apply information.

Perhaps some of the most needed improvements are for individual tree volume/biomass equations, especially for traditionally noncommercial species. Further, there is considerable uncertainty in summarizing the carbon content among the various forest carbon pools (e.g., belowground to forest floor) found across a diversity of forest ecosystems (e.g., tropical to boreal) in the United States. SOC is among these pools, for which limited national-scale data exist to support consistent forest management decision making. Although the soil carbon pool is not expected to change quickly in comparison to live tree pools, in many areas of the United States it is the largest carbon stock (e.g., in northern Minnesota). Beyond reducing the uncertainty associated with estimates of carbon pools, there is ongoing research to refine understanding of the effects of disturbance and climate change on carbon pools.

Another significant area of uncertainty is the ability to influence or predict the influence of forest management activities outside the boundaries of the forest management intervention (e.g., leakage effects). Likewise, there is high variability in estimating substitution effects, especially looking to a future where material manufacturing technologies evolve to be less fossil-fuels-intensive.

5-C.7 Forest Carbon Pool Estimation

As identified through this work and noted in prior discussion, continued research is needed on estimating individual forest carbon pools, especially because they are expected to dynamically respond to climate change. Soil organic carbon is often the largest carbon pool in many forest ecosystems, so its quantification—especially in terms of potential change due to forest management interventions—is paramount. These guidelines omit soil carbon fluxes only because of the lack of sufficient data and research to comprehensively characterize soil carbon response to forest management practices. Likewise, the pools of belowground biomass (e.g., coarse roots) and stumps are critical to informing GHG assessments of forest management activities, especially those related to short-rotation, even-aged silvicultural systems. As with procedures enacted to derive Level 1 approximations of other forest carbon pools (e.g., HWPs), future efforts could apply basic decay functions to belowground biomass and stump pools subsequent to harvests.

As the prior version of these guidelines used the component ratio method (Woodall et al., 2011) to estimate individual tree volume/biomass and this version uses the newly refined NSVB estimators (Westfall et al., 2023), it is expected that allometric refinements will continue through time such that future guideline versions may consider adopting refined carbon fractions and improved individual tree attribute models.

Perhaps the most important advance to be developed in estimating forest carbon pools is the dynamic estimation of forest carbon attributes for any given entity (e.g., forest stand or project) in geospatial systems for rapid knowledge development and transfer. This version of the guidelines derives estimates of forest ecosystem pools by broad domains (e.g., region and forest type) from the national FIADB, such that the associated lookup tables can be rapidly updated via code pipelines between the workbook and the FIADB. Future versions of guidelines and/or applications are expected to be even more dynamic but in a spatially explicit manner. Advances in the research and application of small-area estimation techniques (Prisley et al., 2021) as an approach additional to imputation techniques (Riley et al., 2021) may yield not only authoritative, gridded datasets of forest carbon attributes but also more explicit characterization of error structures.

Chapter 6
Quantifying Greenhouse Gas Sources and Sinks in Managed Wetland Systems

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This chapter has been minimally updated since the 2014 publication of *Quantifying greenhouse gas fluxes in agriculture and forestry: Methods for entity scale inventory*. Therefore, this chapter does not take into consideration any updated literature or methodologies, notably those available in the *2013 supplement to the 2006 IPCC guidelines for national greenhouse gas inventories: Wetlands* (IPCC 2013). This chapter will be revised in future updates of this report.

Suggested chapter citation: Ogle, S.M., P. Hunt, C. Trettin. 2024. Chapter 6: Quantifying greenhouse gas sources and sinks in managed wetland systems. In Hanson, W.L., C. Itle, K. Edquist. (eds.). *Quantifying greenhouse gas fluxes in agriculture and forestry: Methods for entity-scale inventory*. Technical Bulletin Number 1939, 2nd edition. Washington, DC: U.S. Department of Agriculture, Office of the Chief Economist.

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Acronyms, Chemical Formulae, and Units

C	carbon
CH_4	methane
CO_2	carbon dioxide
CO_2-eq	carbon dioxide equivalents
dbh	diameter at breast height
DNDC	Denitrification-Decomposition
EPA	Environmental Protection Agency
FVS	Forest Vegetation Simulator
GHG	greenhouse gas
ha	hectare
IPCC	Intergovernmental Panel on Climate Change
N	nitrogen
N_2O	nitrous oxide
NO_x	mono-nitrogen oxides
NRCS	USDA Natural Resources Conservation Service
P	phosphorous
PRISM	Parameter-Elevation Regressions on Independent Slopes Model
SOC	soil organic carbon
Tg	teragrams
USDA	U.S. Department of Agriculture
USDA-ARS	U.S. Department of Agriculture, Agricultural Research Service

6. Quantifying Greenhouse Gas Sources and Sinks in Managed Wetland Systems

This chapter provides methodologies and guidance for reporting greenhouse gas (GHG) emissions and sinks at the entity scale for managed wetland systems. More specifically, it focuses on methods for managed palustrine wetlands.[1]

- Section 6.1 provides an overview of wetland systems and resulting GHG emissions, system boundaries and temporal scale, and a summary of the selected methods/models and its sources of data.
- Section 6.2 provides the estimation methods for biomass carbon in wetlands and soil carbon, N_2O, and CH_4 emissions and sinks. A single method is provided for each source presented in this chapter (i.e., biomass carbon in forested, shrub, and grass wetlands; soil carbon and CH_4 in wetlands; and direct N_2O emissions in wetlands).
- Appendix 6-A presents the various management practices that influence GHG emissions in wetland systems and land-use change to wetlands.
- Appendix 6-B includes a discussion of research gaps in wetland management.

This chapter and its methods have been minimally updated since the 2014 report. Therefore, this chapter does not take into consideration any updated literature or methodologies, notably those available in the *2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands* (IPCC 2013). Revisions will be made to this chapter in future report updates. Additional background information on the impact of cropland and grazing land management is available in the 2014 report.

6.1 Overview

Wetlands occur across most landforms, existing as natural unmanaged and managed lands, restored lands following conversion from another use (typically agriculture), and as constructed systems for water treatment, such as anaerobic lagoons. All wetlands sequester carbon and are a source of GHGs. Table 6-1 describes the sources of emissions or sinks and the gases estimated in the methodology.

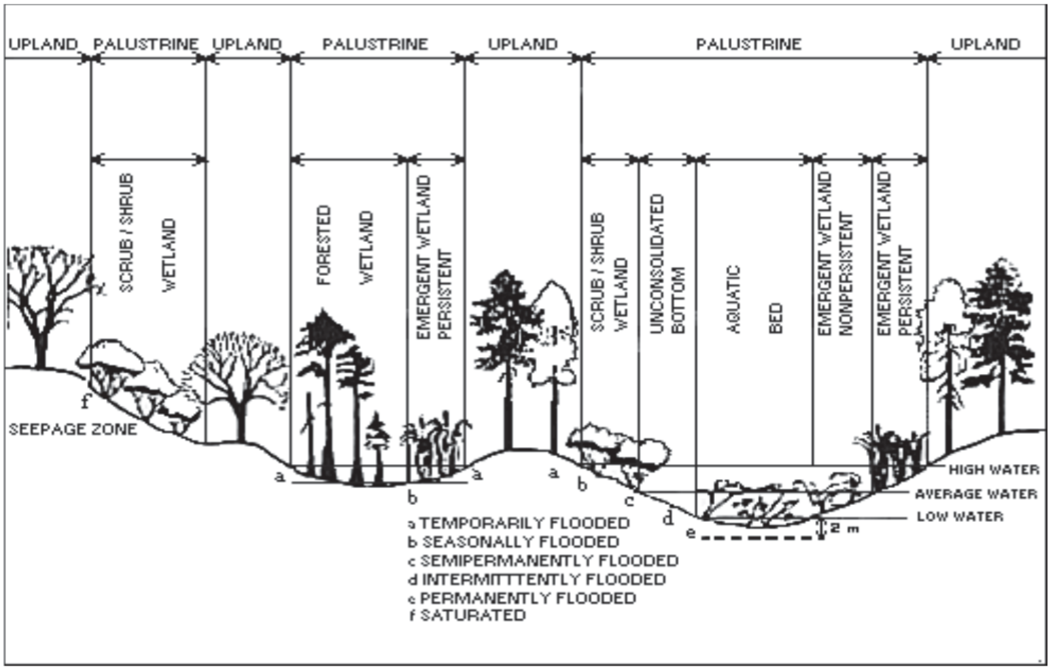
[1] Palustrine wetlands include nontidal and tidal wetlands that are primarily composed of trees, shrubs, persistent emergent, emergent mosses, or lichens, where salinity due to ocean-derived salts is below 0.5 ‰ (parts per thousand). Palustrine wetlands also include those wetlands lacking vegetation that have the following four characteristics: (1) are less than 20 acres; (2) do not have active wave-formed or bedrock shorelines; (3) have a maximum water depth of less than 6.5 ft. at low water; and (4) have a salinity due to ocean-derived salts less than 0.5 percent (Stedman and Dahl, 2008).

Table 6-1. Overview of Wetland Systems Sources and Associated Greenhouse Gases

Source	Method for GHG Estimation			Description
	CO_2	N_2O	CH_4	
Biomass carbon	✓			Provisions for estimating aboveground biomass for wetland forests and above and belowground biomass and carbon are included for shrub and grass wetlands in this chapter. Aboveground biomass for forested wetlands and shrub and grass wetlands includes live vegetation, trees, shrubs, and grasses, standing dead wood (dead biomass), and down dead organic matter—litter layer (dead biomass).
Soil C, N_2O, and CH_4 in wetlands	✓	✓	✓	The production and consumption of carbon in wetland-dominated landscapes are important for estimating the contribution of GHGs, including CO_2, CH_4, and N_2O emitted from those areas to the atmosphere. The generation and emission of GHGs from wetland-dominated landscapes are closely related to inherent biogeochemical processes, which also regulate the carbon balance (Rose and Crumpton, 2006). However, those processes are highly influenced by land use, vegetation, soil organisms, chemical and physical soil properties, geomorphology, and climate (Smemo and Yavitt, 2006).

6.1.1 Description of Sector

The National Wetlands Inventory, available through the U.S. Fish and Wildlife Service, provides information on wetland habitats in the United States via the wetlands geospatial dataset and wetland status and trends reports, both determined via remote sensing technology. Cowardin et al. (1979) defines wetlands and broadly classifies them into five major systems: (1) marine, (2) estuarine, (3) riverine, (4) lacustrine, and (5) palustrine. Four of those systems (marine, estuarine, riverine, and lacustrine) are open-water bodies and are not considered within the methods described in this guidance. Palustrine wetlands encompass the wetland types occurring on the land and are further classified by major vegetative life forms and wetness or flooding regime. Common palustrine wetlands are illustrated in figure 6-1. For example, forested wetlands are often classified as palustrine—forested. Similarly, most grass wetlands are classified as palustrine—emergent, reflecting emergent vegetation (e.g., grasses and sedges). Wetlands also vary greatly with respect to groundwater and surface water interactions that directly influence hydroperiod (i.e., the length of time and portion of the year the wetland holds water), water chemistry, and soils (Cowardin et al., 1979; Winter et al., 1998). All these factors along with climate and land-use drivers influence the overall carbon balance and GHG fluxes.



Source: Cowardin et al. (1979).

Figure 6-1. Palustrine Wetland Classes Based on Vegetation and Flooding Regime

Grassland and forested wetlands are subject to a wide range of land use and management practices that influence the carbon balance and GHG flux (Faulkner et al., 2011; Gleason et al., 2011). For example, forested wetlands may be subject to silvicultural prescriptions with varying intensities of management through the stand rotation; hence, the carbon balance and GHG emissions should be evaluated on a rotation basis, which could range from 20 to more than 50 years. In contrast, grass wetlands may be grazed, hayed, or directly cultivated to produce a harvestable commodity annually. While each management practice may influence carbon sequestration and GHG fluxes, the effect is dependent on vegetation, soil, hydrology, climatological conditions, and management prescriptions. This section focuses on restoration and management practices associated with palustrine wetlands that are typically forested or grassland.

6.1.2 Resulting GHG Emissions

GHG emissions from wetlands are largely controlled by water table depth and duration as well as climate and nutrient availability. Under aerobic soil conditions, which are common in most upland ecosystems, organic matter decomposition releases CO_2, and atmospheric CH_4 can be oxidized in the surface soil layer (Trettin et al., 2006). In contrast, the anaerobic soils that characterize wetlands can produce CH_4 (depending on the water table position) in addition to emitting CO_2. Accordingly, wetlands are an inherent source of CH_4, with globally estimated emissions of 55 to 150 teragrams (Tg) of CH_4 per year (Blain et al., 2006).

Biomass carbon can change significantly with the management of wetlands, particularly in forested wetlands, changes from forest to wetlands dominated by grasses and shrubs, or open water. In forested wetlands, there can also be significant carbon in dead wood, coarse woody debris, and fine litter. Harvesting practices will also influence the carbon stocks in wetlands to the extent the wood is collected for products, fuel, or other purposes.

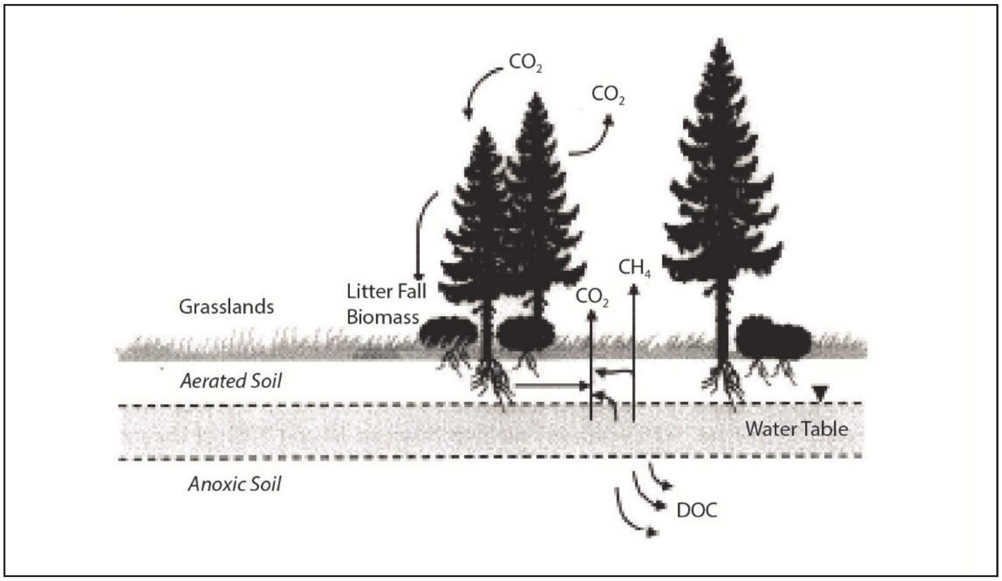
Wetlands are also a source of soil N_2O emissions, primarily because of nitrogen runoff from adjoining uplands and leaching into groundwater from agricultural fields and/or animal production facilities. N_2O emissions from wetlands due to nitrogen inputs from surrounding fields or animal products are considered indirect emissions of N_2O (de Klein et al., 2006). Methodologies for estimating indirect N_2O are provided in the respective source chapter (i.e., chapter 3 or chapter 4). However, direct N_2O emissions occur in wetlands if management practices include nitrogen fertilization, hence, guidance is provided for this source of emissions.

6.1.3 Risk of Reversals

Wetlands inherently accumulate carbon in the soils due to anaerobic conditions, and they are natural sources of CO_2 and CH_4 in the atmosphere. Management may alter conditions that affect both the pools and fluxes. For example, accumulated soil carbon can be returned to the atmosphere if the wetland is drained (Armentano and Menges, 1986). In contrast, silvicultural water management in wetlands can lead to higher biomass production, which may partially offset increased soil organic matter oxidation. Conversely, the soil carbon pool in converted wetlands is typically lower than the unmanaged soil, and restoring wetland conditions may increase carbon storage over time if inherent hydric soil conditions are maintained with consistent organic matter inputs.

Reversals of emission trends can occur if a manager reverts to a prior condition or an earlier practice. For example, an entity may decide to return a wetland that had been drained and cropped back to a forested wetland condition. Another common example would be if a restored forested wetland reverted to agriculture. These reversals do not negate the mitigation of CH_4 or N_2O emissions to the atmosphere that had occurred previously, to the extent that wetland restoration or change in management can reduce or change these emissions. Correspondingly, the starting point from the reversion will determine the effect on carbon sequestration and GHG flux. For example, in a restored forested wetland, reversion of the site to crop production would return carbon sequestered during the restoration period to the atmosphere over time.

There is a trade-off in CH_4 and N_2O emissions with the management of the water table position. Wetlands with anaerobic soil conditions that are persistent near the surface for a longer period during the year will tend to have higher CH_4 emissions and lower emissions of N_2O. N_2O emissions are greatly reduced if soils are saturated because there is little inherent nitrification, and denitrification will lead to N_2 production (Davidson et al., 2000). For example, restoration of wetlands will normally lead to a higher water table for a longer period of the year and thus contribute to higher emissions of CH_4 but lower emissions of N_2O. These trends can be reversed if the water table is lowered through management or drought, which will tend to enhance N_2O emissions if there is a source of nitrate while reducing emissions of CH_4. Figure 6-2 provides an illustration of the carbon cycle typically found in wetland forests and grassland wetlands and represents the scope of the methods presented in this guidance.



Source: Trettin and Jurgensen (2003).

Figure 6-2. Carbon Cycle for Forest and Grassland Wetlands

6.1.4 System Boundaries and Temporal Scale

System boundaries are defined by the coverage, extent, and resolution of the estimation methods. The location of the wetlands may be approximated by use of the National Wetlands Inventory (FWS, 2022), the location of hydric soils as conveyed by the NRCS soils map, or through direct delineation of wetlands. The coverage of the methods can be used to estimate a variety of emission sources, including emissions associated with biomass C, litter C, and soil carbon stock changes and CO_2, CH_4, and N_2O fluxes from soils. System boundaries are also defined by the extent and resolution of the estimation method. The methods provided for wetlands have a spatial extent that would include all wetlands in the entity's operation, with estimation occurring at the resolution of an individual wetland. Emissions are estimated on an annual basis for as many years as needed for GHG emissions reporting.

6.1.5 Summary of Selected Methods

This chapter provides methods for estimating carbon stock changes and CH_4 and N_2O emissions from naturally occurring wetlands and restored wetlands on previously converted wetland sites.[2] Constructed wetlands for water treatment, including detention ponds, are engineered systems that are beyond the scope considered here because they have specific design criteria for influent and effluent loads. In addition, the methods are restricted to the estimation of emissions on palustrine wetlands that are influenced by a variety of management options such as water table management, timber, or other plant biomass harvest, and wetlands that are managed with fertilizer applications. The methods are based on established principles and represent the best available science for estimating changes in carbon stocks and GHG fluxes associated with wetland management activities. However, given the wide diversity of types of wetlands and the variety of management regimes, the basis for the methods provided in this section is not as well-developed as other chapters in this report (i.e., Cropland and Grazing Lands, Animal Production, and Forestry

[2] Wetlands that are converted to a nonwetland status should be considered in the appropriate chapter (e.g., Cropland and Grazing Lands, Animal Production Systems, and Managed Forest Systems).

Methods). Table 6-2 provides a summary of the methods and their corresponding section for the sources of emissions estimated in this report.

The data required to apply these methods range from basic information on soils, vegetation, weather, land use, and management history to data on fertilization rates or drainage conditions. While some of these data are operation-specific and must be provided by the entity, other data can be obtained from national databases, such as weather data and soil characteristics.

Table 6-2. Overview of Wetland Systems Sources, Method, and Section

Section	Source	Method
6.2.1	Biomass carbon	Methods for estimating forest vegetation and shrub and grassland vegetation biomass carbon stocks use a combination of the Forest Vegetation Simulator (FVS) model and lookup tables for dominant shrub and grassland vegetation types found in chapter 3. If there is a land-use change to agricultural use, methods for cropland herbaceous biomass are provided in chapter 3.
6.2.2	Soil C, N_2O, and CH_4 in wetlands	The Denitrification-Decomposition (DNDC) process-based biogeochemical model is the method used for estimating soil C, N2O, and CH4 emissions from wetlands. DNDC simulates the soil carbon and nitrogen balance and generates emissions of soil-borne trace gases by simulating carbon and nitrogen dynamics in natural and agricultural ecosystems (Li et al., 2000; Miehle et al., 2006; Stang et al., 2000) and forested wetlands (Dai et al., 2011; Zhang et al., 2002), using plant growth estimated as described in section 6.2.1.

6.2 Estimation Methods

Section 6.2.1 provides methods for estimating live and dead biomass in forested, shrub, and grassland wetlands. Section 6.2.2 provides methods for estimating soil C, N_2O, and CH_4 emissions from managed naturally occurring wetlands.

6.2.1 Biomass Carbon in Wetlands

Method for Estimating Live and Dead Biomass Carbon in Wetlands

- Methods for estimating forest vegetation and shrub and grassland vegetation biomass carbon stocks use a combination of the Forest Vegetation Simulator model and the biomass carbon stock changes method in section 3.2.1 of chapter 3. If there is a land-use change to agricultural use, use the chapter 3 methods for cropland herbaceous biomass.

6.2.1.1 Description of Method

Provisions for estimating aboveground biomass for wetland forests and aboveground and belowground biomass and carbon are included for shrub and grass wetlands in this section. Since the vegetative cover on wetlands may vary from natural communities to agricultural crops, cross-references are made to ensure congruity with chapter 3 and chapter 5.

Forest vegetation: Biomass carbon stocks are estimated for forests in wetlands using the methods described in chapter 5. The 'Level 3' approach uses the FVS, which is a system of growth and yield models that estimate growth and yield for U.S. forests. FVS is an individual tree model and can estimate biomass carbon stock change for nearly any type of forest stand. The Fire and Fuels Extension to FVS can be used to generate reports of all live and dead biomass carbon pools in addition to harvested wood products. Regional variants are available for FVS that allow for region-specific focus on species and forest vegetation communities. The driver for productivity is the availability of site index curves,[3] and the regional variants include many wetland tree species. Regional variants of FVS may also provide provisions for refining the basis for estimating productivity by classifying the area of interest into ecological units, habitat types, or plant associations. However, if a species-specific curve is not available, then a default function is used to estimate carbon stock changes.

Grassland vegetation: The change in carbon stock for grass wetlands is generally small unless there are drought conditions, or the area is actively managed. However, changes can be significant with a land-use change. Therefore, biomass carbon stock changes can be estimated following a land-use change using the method in section 3.2.1 of chapter 3.

6.2.1.2 Activity Data

Forested wetlands: The data and requirements for estimating the changes in carbon stocks in wetland forests are the same as those described for upland forests in chapter 5.

Grassland vegetation: The data and requirements for estimating the changes in carbon stocks in grassland vegetation are the same as those described for total biomass carbon stock changes presented in chapter 3.

6.2.1.3 Model Output

Changes in aboveground carbon pools associated with wetland forests are provided for live vegetation, standing dead biomass, and down dead biomass. Change in live biomass carbon is also provided for belowground biomass. The units of reporting are metric tonnes/ha CO_2-eq.

6.2.1.4 Limitations and Uncertainty

Estimates of the forest biomass carbon pools in wetlands are constrained by limited data on productivity response to management and are sensitive to the wide array of characteristic vegetative communities and soil types. Although FVS is the most inclusive model available, many results for wetlands will still be based on default model functions, because there is limited data on the growth of specific wetland species under particular management regimes. Accordingly, the results will provide a relative basis for tracking changes over time in biomass carbon. Table 6-3 summarizes additional limitations of the current approach.

Table 6-3. Key Limitations to Estimating Biomass Carbon Pools in Forest Wetland Vegetation

Consideration	Limitation
Ratio for belowground biomass	A ratio is used to estimate belowground biomass in upland and wetland forests based on aboveground biomass. While a common ratio will provide a basis for estimating relative change, it will likely over or underestimate actual stocks in many wetlands.
Response to management or climatic conditions	Wetland vegetation is known to respond to management practices, soil, and climatic conditions. Those relationships are not necessarily reflected in FVS because there is an insufficient basis for generalized assessment purposes. For example, in response to dynamic water-level fluctuations during wet and dry

[3] Site index is the measure of a forest's potential productivity. The height of the dominant or co-dominant trees at a specified age in a stand are calculated in an equation that uses the tree's height and age. Site index equations differ by tree species and region. Site index curves are constructed by using the tree heights at a base age and an equation is derived from the curves to estimate the site index when an individual tree's age is not the same as the base age (Hanson et al., 2002).

Consideration	Limitation
	cycles, wetlands often exhibit major intra- and interannual shifts in vegetative structure, ranging from open water to emergent herbaceous vegetation. Correspondingly, the altered site conditions under the management regime and the genetic quality of the planted trees may exhibit responses that are not captured by the existing allometric relationships in FVS.

The shrub and herbaceous biomass method is based on the assumptions found in chapter 3.

Major sources of uncertainty include belowground biomass, vegetation response to management, and hydrologic regime (e.g., seasonal hydroperiod). Uncertainty in herbaceous carbon stock changes will result from a lack of precision in crop or forage yields, residue-yield ratios, root-shoot ratios, and carbon and carbon fractions, as well as the uncertainties associated with estimating the biomass carbon stocks for the other land uses.

Measurement, sampling, and regression/modeling errors are all part of the estimation process in FVS. Some similar measure of the representativeness of selected forest inventory and analysis plots to the entities' forests is needed. Uncertainties about carbon conversion factors are also significant in some cases.

6.2.2 Soil C, N_2O, and CH_4 in Wetlands

Method for Estimating Soil C, N_2O and CH_4 in Wetlands

- The DNDC process-based biogeochemical model is the method used for estimating soil C, N_2O, and CH_4 emissions from wetlands.
- DNDC predicts soil carbon and nitrogen balance and the generation and emission of soil-borne trace gases by simulating carbon and nitrogen dynamics in natural and agricultural ecosystems (Li et al., 2000; Miehle et al., 2006; Stang et al., 2000) and forested wetlands (Dai et al., 2011; Zhang et al., 2002), using plant growth estimatedas described in section 6.2.1.

6.2.2.1 Description of Method

The method consists of using the process-based model—DNDC—to estimate the changes in soil organic carbon (SOC) stocks, CH_4, and N_2O emissions, based on the standing biomass and plant growth that are provided by the vegetation method outlined above (section 6.2.1), wetland characteristics, and the planned management activities. The model simulates SOC stocks, CH_4, and N_2O emissions at the beginning of the reporting period based on an assessment of initial conditions at the site; then the model simulates the reporting period based on the current/recent management activity and any changes in the wetland conditions. This information characterizes the physical and chemical soil properties that in turn interact with the climatic regime, management practices, and vegetation response. The reported emissions for the land parcel must reflect the total for the entire land area. Accordingly, the per-unit area emission rates from DNDC are expanded based on the total wetland area for the land parcel to estimate total emissions.

Use equation 6-1, equation 6-2, and equation 6-3 to estimate SOC stock changes, CH_4 emissions, and N_2O emissions from a parcel of land in a wetland, respectively. Global warming potentials are provided in chapter 2.

Equation 6-1: Change in SOC Stocks for Wetlands

$$\Delta C_{soil} = (SOC_t - SOC_{t-1}) \times A \times CO_2MW$$

Where:

ΔC_{soil}	=	annual change in mineral soil organic carbon stock (metric tons CO_2-eq/year)
SOC_t	=	soil organic carbon stock at the end of the year (metric tons C/ha)
SOC_{t-1}	=	soil organic carbon stock at the beginning of the year (metric tons C/ha)
A	=	area of parcel (ha)
CO_2MW	=	ratio of molecular weight of CO_2 to C, 44/12 (dimensionless)

Equation 6-2: CH_4 Emissions from Wetlands

$$CH_{4Wetlands} = ER \times A \times CH_4MW \times CH_{4GWP}$$

Where:

$CH_{4Wetlands}$	=	total CH_4 emissions from managed wetlands for the parcel (metric tons CO_2-eq/year)
ER	=	emission rate on a per unit wetland area (metric tons CH4-C/ha/year)
A	=	area of the parcel (ha)
CH_4MW	=	conversion of CH_4-C to C, 16/12 (dimensionless)
CH_{4GWP}	=	global warming potential for CH_4 (metric tons CO_2-eq/metric tons CH_4)

Equation 6-3: N_2O Emissions from Wetlands

$$N_2O_{Wetlands} = ER \times A \times N_2O_{MW} \times N_2O_{GWP}$$

Where:

$N_2O_{Wetlands}$	=	total N_2O emissions from managed wetlands for the parcel (metric tons CO_2-eq/year)
ER	=	emission rate on a per unit land area (metric tons N_2O-N/ha/year)
A	=	area of the parcel (ha)
N_2O_{MW}	=	conversion of N_2O-N to N_2, 44/28 (dimensionless)
N_2O_{GWP}	=	global warming potential for N_2 O (metric tons CO_2-eq/metric tons N_2O)

To estimate the SOC stock changes, CH_4, and N_2O emissions, DNDC requires a considerable amount of information to characterize the plant production (section 6.2.1), wetland characteristics, and management activities. The initial step in applying the method is to parameterize DNDC using the baseline soil conditions, along with the corresponding forest or grassland conditions. For example, if a forest plantation is to be harvested and regenerated during the reporting period, the initial conditions should reflect the preharvest conditions. Based on the initial conditions, the model simulates baseline fluxes and the SOC stock prior to the reporting period for the entity.

Subsequently, the entity specifies the type of management activity(s) changes that occurred during the reporting period (if any occurred). Provisions are available to have multiple management activities on a single tract if there were mixed activities. Climatic factors, especially precipitation, can affect carbon turnover and wetland conditions. Consequently, weather data are a key input to DNDC, and will be provided from a climatological data set.

The simulation output at the end of each year is used to estimate the change in SOC stocks and the total amount of CH_4 and N_2O emissions for the year. Annual changes in SOC can be estimated based on the difference between years, and the total change in emissions can be estimated by combining the changes in SOC pools with the annual CH_4 and N_2O flux.

6.2.2.2 Activity Data

Activity data for the application of DNDC are summarized in table 6-4. Vegetation management information affects the amount of organic matter that is available for decomposition processes. Water management information conveys how the drainage system affects the soil water table dynamic as compared to an undrained condition. Soil tillage information is used to convey when the surface soil is disturbed, or its elevation changed because of the associated effects on decomposition. The fertilization information is needed because the addition of nitrogen greatly affects decomposition and N_2O production. In addition, land-use history influences the amount of soil organic carbon. If an entity is composed of different wetland types, it is recommended that separate estimates be prepared because the carbon turnover rate and GHG emissions can vary widely depending on hydric soil properties and the type of vegetation.

Table 6-4. Activity Data for Application of DNDC

Category	Management Practice	Data
Vegetation management	Grazing or management events should be included to capture the influence on carbon input to soils and subsequent effects on the soil carbon stocks.	▪ Harvesting: date, harvest, or cut fraction ▪ Understory thinning or chopping: date, chopped fraction ▪ Prescribed fire: date, the proportion of forest floor, and understory consumed ▪ Tree planting: date, species, density
Water management regime	Water table response to the drainage system, daily data.	▪ Drainage system: date, controlled water table elevation
Soil management	Application of soil amendments or site preparation practices for tree planting.	▪ Type of site preparation
Fertilization practices	Applications of mineral or organic nitrogen fertilizers will be needed to simulate the effect on N_2O emissions.	▪ Fertilization frequency, date, application rate (N, P kg/ha)

Category	Management Practice	Data
Land-use history	Summary of land-use practices over the past 5 years. For assessing if prior use affects parameterization. The time since a change in land management practice for assessing effects on decomposition.	▪ Fertilization regimes, drainage regimes, cropping, or forest management history.

6.2.2.3 Ancillary Data

The DNDC model requires relatively detailed information about the site (table 6-5). While default values are available for most parameters, some entity-specific data are needed to produce reasonable estimates. Most of the required soil input data are available from the national soils database (NCSS, 2022). Similarly, climate data are available from the Parameter-Elevation Regressions on Independent Slopes Model, or PRISM (PRISM Climate Group, 2018).

Table 6-5. Input Information Needed for the Application of DNDC

Category	Data
Climate	Daily maximum and minimum temperature, daily rainfall; nitrogen deposition in rainfall, or use the default value.
Vegetation	Standing biomass and biomass and detrital inputs are provided in section 6.2.1; belowground biomass is estimated based on aboveground biomass.
Soil	Hydraulic parameters and physical and chemical components, including thickness; layers; hydraulic conductivity; porosity; field capacity; wilting point; carbon content; pH; organic matter fractions; content of stone, sand, silt, and clay; and bulk density for major soil layers.
Hydrology	The water table below the surface is the daily input or starting position and DNDC can estimate GHG emissions and sinks using empirical functions.

6.2.2.4 Model Output

Model output includes annual estimates of CH_4, N_2O emissions, and changes in soil organic carbon stocks. The units of reporting are metric tons CO_2-eq/ha.

6.2.2.5 Limitations and Uncertainty

The models to estimate biomass carbon stock change in vegetation are robust with respect to species and community composition. However, uncertainties may be higher than for uplands because of limited background information. The merit of the recommended approach is that it ensures consistency for estimating changes in the vegetative carbon pool among land types and uses by using common methods as described in section 6.2.1. However, this approach complicates the application of DNDC for estimating changes in soil carbon pools and fluxes because it contains provisions for sequestering carbon in crops, grasslands, and forest vegetation. Accordingly, DNDC would have to undergo substantial revisions to accommodate the vegetative component as an input variable because the vegetation growth functions are integral to the consideration of hydrologic processes (especially evapotranspiration) and biogeochemical processes. The DNDC model could be used as a stand-alone tool for wetlands, but unfortunately, the production or biomass carbon functions have not been validated for many of the wetland plant communities.

The availability of water table data is essential to modeling the carbon cycle in wetland soils. Since the lack of site-specific water table data for a sufficient period is likely a constraint for most entities, an approach incorporating a hydrologic module or look-up table is needed. Hydrologic models that provide information on water table dynamics are inherently complex, but they can be effective (Dai. et al., 2010). Accordingly, the development of characteristic water table conditions for a range of climatological and soil settings would be a viable approach that can also incorporate water management effects (e.g., Skaggs et al., 2011).

Tidal freshwater forested wetlands, which occur to a limited extent along the Atlantic, Gulf, and Pacific coasts, are a special case. The tidal influence on water table dynamics can make characterizing the water table regime of such sites more difficult. For DNDC to simulate the carbon dynamics would require detailed data on daily water table dynamics, and such detailed data are unavailable.

While the effects of the various management regimes on soil carbon pools and GHG fluxes have not been widely studied, this is more of a consideration with respect to uncertainties in the estimates as opposed to a limitation to its application. The DNDC framework is robust because it is a process-based model that has been validated in a wide variety of wetland types and soils. However, it has not been extensively tested on Histosols or peat soils, especially with respect to changes in soil carbon stocks. The model was validated successfully for estimating CH_4 from microtopographic positions in a peatland (Zhang et al., 2002), but additional work is needed to better address the wide array of managed Histosols that exist across the country.

Similarly, this method is not applicable to constructed wetlands, impoundments, or shallow reservoir systems that have extended periods of ponding; those sites would tend to have dynamics more similar to a lake or pond as opposed to a terrestrial ecosystem.

Concerning the forest model, the accuracy of the estimates is dependent on the applicability of the available site index curves. While the general curves are available for all species, they may not accurately represent the site or the entity's management regime. Provisions are included within FVS for customizing the tree site index curves, which could be important for an entity, especially if genetically improved planting stock and fertilization regimes are employed.

Detrital organic matter is the source of decomposition processes. The effect of vegetation on wetland carbon dynamics is promulgated through the amount of organic matter and the water regime (e.g., evapotranspiration). Accordingly, the accuracy of the vegetation productivity and turnover will affect the estimates of the soil carbon pools and GHG flux.

Water table position is the most critical factor affecting CH_4 and N_2O flux from the wetland soil (Trettin et al., 2006). Accordingly, considerations to improve that estimate as discussed in section 6.2.2 will improve the estimates of GHG emissions from the soil. There are other uncertainties in the activity and ancillary data, as well as a model structure that can create bias and imprecision in the resulting estimates. Wetlands typically exist in a mosaic with upland forests, grasslands, and cultivated lands. Accordingly, the accuracy of partitioning the entity into upland (agriculture, forest) and wetlands will affect the accuracy of the estimates.

6.3 Chapter 6 References

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Appendix 6-A: Method Documentation

6-A.1 Biomass Carbon in Wetlands

6-A.1.1 Rationale for Method

Various approaches are used for estimating tree biomass carbon, but ultimately each relies on allometric relationships developed from a characteristic subset of trees. The FVS is offered for the "Level 3" approach to estimate tree biomass. FVS is model-based approach that is specific to United States conditions and a Tier 3 method as defined by the IPCC. The simulator is the most complete model in the United States to estimate tree biomass. Regional versions of FVS have been refined based on large databases developed from many years of data collection on forest stands throughout the United States, thereby providing improved estimates while requiring few input parameters from the user.

Both IPCC (Ogle et al., 2019) and the U.S. EPA (2020) consider herbaceous biomass carbon stocks to be ephemeral and recognize that there are no net emissions to the atmosphere following crop growth and senescence during one annual crop cycle (West et al., 2011). However, with respect to changes in land use (e.g., forest to cropland), IPCC (Ogle et al., 2019) recommends that cropland biomass be counted in the year that land conversion occurs, and the same assumption also applies for grassland (McConkey et al., 2019). According to IPCC, estimating the herbaceous biomass carbon stock during changes in land use is necessary to quantify the influence of herbaceous plants on CO_2 uptake from the atmosphere and storage in the terrestrial biosphere. However, this method does not recognize changes in herbaceous biomass that occur with changes in crop rotations, nor does it recognize long-term increases in annual crop yields. The method in this chapter is considered a Tier 2 method as defined by IPCC because it incorporates factors that are based on United States-specific data and differs from the methodology in U.S. EPA (2020) because of this.

The methods presented in this section are based on the following definitions.

- *Live vegetation biomass:* Live vegetation includes trees, shrubs, and grasses. The tree carbon pool includes aboveground and belowground carbon mass of live trees, and the aboveground biomass of the forest understory is defined in section 5.1.3. The methods to estimate full-tree and aboveground biomass for trees greater than one inch in diameter at breast height (dbh) are based on the models provided in the forest section.

The forest understory vegetation includes all biomass of undergrowth plants in a forest, including woody shrubs and trees less than one inch in dbh.

- *Standing dead wood (dead biomass)*: The carbon pool of standing deadwood in a forested wetland is defined and estimated according to the methods in chapter 5.
- *Down dead organic matter—litter* layer *(dead biomass)*: Down dead organic matter includes the litter layer composed of small pieces of dead wood, branches, leaves, and roots in various stages of decay. This layer is typically designated as the organic layer of the soil. This pool also includes logs in various stages of decay that lie on the soil surface (e.g., down-dead wood, forest floor or litter).

6-A.2 Soil C, N2O, and CH_4 in Wetlands

6-A.2.1 Rationale for Method

The production and consumption of carbon in wetland-dominated landscapes are important for estimating the contribution of GHGs, including CO_2, CH_4, and N_2O emitted from those areas to the atmosphere. The generation and emission of GHGs from wetland-dominated landscapes are closely related to inherent biogeochemical processes that also regulate the carbon balance (Rose and Crumpton, 2006). However, those processes are highly influenced by the land use, vegetation, soil organisms, chemical and physical soil properties, geomorphology, and climate (Smemo and Yavitt, 2006).

Given this complexity, a process-based modeling approach is desirable because these approaches typically account for more of the variability than simpler emission factor methods (IPCC, 2006). However, few process-based models have been tested sufficiently to be used for operational reporting of GHG emissions. One of the more widely tested models for estimating GHG fluxes from wetlands is the DNDC model. DNDC is a process-based biogeochemical model that is used to predict plant growth and production, carbon and nitrogen balance, and generation and emission of soil-borne trace gases by means of simulating carbon and nitrogen dynamics in natural and agricultural ecosystems (Li et al., 2000; Miehle et al., 2006; Stang et al., 2000) and forested wetlands (Zhang et al., 2002). The model is designed to explicitly consider anaerobic biogeochemical processes, which are fundamental to addressing soil carbon dynamics and trace GHG dynamics in wetlands (Trettin et al., 2001). It integrates decomposition, nitrification–denitrification, photosynthesis, and hydro-thermal balance within the ecosystem. These components are mainly driven by environmental factors, including climate, soil, vegetation, and management practices.

DNDC has been tested and used for estimating GHG emissions from forested ecosystems in a wide range of climatic regions, including boreal, temperate, subtropical, and tropical (Kesik et al., 2006; Kiese et al., 2005; Kurbatova et al., 2008; Li et al., 2004; Stang et al., 2000; Zhang et al., 2002), and similarly for grasslands and cultivated wetlands (Giltrap et al., 2010; Rafique et al., 2011).

Appendix 6-B: Summary of Research Gaps for Managed Wetland Systems.

Wetland management, and its influence on GHG emissions, is not as well studied as some of the other management practices in this report, such as tillage in croplands or forest harvesting practices in uplands. There is the potential for improving the estimation of GHG emissions associated with different management practices in the future if there are monitoring activities and studies to fill information gaps. A select number of information needs and research gaps are identified here.

- The 2013 Supplement to the 2006 Intergovernmental Panel on Climate Change (IPCC) Guidelines provide new guidance for estimating emissions from drained inland organic soils, rewetted organic soils, coastal wetlands, inland wetland mineral soils, and constructed wetlands for wastewater treatment (Blain et al., 2013). These newly developed guidelines will be compared to the technical methods provided in this report.
- Water table position is the principal factor affecting carbon dynamics in wetlands; unfortunately, while estimates of water table depth are provided in the Web Soil Survey, there is a lack of long-term data, which is needed to characterize the water table response to a management regime and to provide a basis for validating assessment tools. Establishment of a network of water table monitoring sites within selected USDA, Forest Service experimental forests and ranges and USDA, Agricultural Research Service (ARS) experiment stations could provide the continuity in measurements and linkages with common management practices to represent the major soil and climatic condition in the United States.
- Improving modeling capabilities that integrate surrounding areas with the wetlands that receive surface and subsurface drainage waters will allow for modeling the flows of nutrients and organic matter into wetlands and subsequent losses to other wetlands beyond the entity's operation. This type of assessment framework is used in several established spatially explicit hydrologic models; the need is to integrate the biogeochemistry. Linked models can be used at present; but development of a functionally integrated system is needed to support broad-based applications.
- While the National Range and Pasture Handbook provides methods for determining and estimating site-specific biomass, there is a need, generally, for improved information on biomass production and allocation in managed wetlands. These data could be obtained through a coordinated monitoring program employing USDA, Forest Service experimental forests and ranges, USDA, ARS experiment stations, and U.S. Department of the Interior wildlife refuges to monitor production of key species or vegetation types in association with common management prescriptions. There is also need for more detailed mechanistic research to provide information on energy, water, and GHG dynamics on selected managed sites; this information is critical for validating process-based models.
- Field-based studies are needed to develop more complete databases that provide ancillary data for GHG estimation, particularity CH_4 emissions for DNDC or similar process-based models, rather than relying on entity input, which will likely be challenging. A key attribute of this work should be the consideration of the inherent spatial and temporal variability within a site.
- Further quantification of the controlling and threshold parameters and associated uncertainty within DNDC or similar process-based models to estimate trace gas emissions is

warranted. This work could also suggest a path towards development of an assessment tool that was not reliant on a wide array of parameters to effectively simulate the GHG dynamics of the site.

- A more robust and extensive database on GHG emissions from freshwater tidal (salinity <0.5 percent) palustrine wetlands is needed to more fully understand the drivers of emissions, in addition to providing a more complete dataset for parameterization and evaluation of process-based models.
- Studies on individual sites and meta-analyses of existing data are needed to fully evaluate the net GHG flux for CH_4, N_2O, and soil carbon. Most studies only consider one of the GHGs and may mask some of the differences in fluxes among the GHGs associated with a management activity.

This list is not exhaustive but is intended to provide some direction for improving the estimation methods for GHG emission from wetlands.

Chapter 7
Quantifying Greenhouse Gas Sources and Sinks From Land-Use Change

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Acronyms, Chemical Formulae, and Units

C	carbon
CH_4	methane
CO_2	carbon dioxide
CO_2-eq	carbon dioxide equivalents
DOM	Dead organic matter
GHG	greenhouse gas
ha	hectare
IPCC	Intergovernmental Panel on Climate Change
N_2O	nitrous oxide
PRISM	Parameter-Elevation Regressions on Independent Slopes Model
SOC	soil organic carbon
SSURGO	Soil Survey Geographic Database
USDA	U.S. Department of Agriculture
U.S. EPA	U.S. Environmental Protection Agency

7. Quantifying Greenhouse Gas Sources and Sinks From Land-Use Change

This chapter provides methodologies and guidance on estimating the net greenhouse gas (GHG) flux resulting from changes between land-use types—i.e., conversions into and out of cropland, wetland, grazing land, or forestland—at the entity scale:

- Section 7.1 provides a brief overview of land use.
- Section 7.2 provides the methods for estimating emissions or annual carbon stock changes for land-use change.

The appendixes that accompany this chapter are:

- Appendix 7-A provides the rationale for the methods.

Table 7-1 describes the sources covered in this chapter, along with the corresponding GHGs. As needed, refer to chapter 2 for land use background or definitions.

Table 7-1. Overview of Land-Use Change Sources and Associated GHGs

Section	Source	Method for GHG Estimation			Description
		CO_2	N_2O	CH_4	
7.2.1	Annual change in biomass carbon stocks due to land conversion	✓			Live biomass carbon stocks constitute a significant carbon sink in many forest and some agricultural lands.
7.2.2	Annual change in carbon stocks in dead wood and litter due to land conversion	✓			Dead organic matter (DOM) carbon stocks occur in dead wood and litter, and may constitute a significant carbon sink, particularly in forest lands.
7.2.3	Change in SOC stocks for mineral soils and organic soils due to land use conversion	✓			Soil organic carbon (SOC) stocks are influenced by land-use change (Aalde et al., 2006). The most significant changes in SOC occur with land-use conversions to croplands, due to changes in the disturbance regimes and associated effects on soil aggregate dynamics (Six et al., 2000), or due to drainage of the soil if previous land use was a wetland.

7.1 Overview

In many cases, the methods for estimating GHG flux resulting from land-use change are the same as those used to estimate carbon stock changes in the chapters on cropland and grazing land, forestry, and wetlands (chapters 3, 5, and 6 respectively). This chapter provides additional guidance on those methods and, in some cases, this chapter also provides guidance on reconciling carbon stock estimates between discrete data sets and estimation methods (e.g., reconciling forest soil carbon estimates and cropland soil carbon estimates for land-use change from forest land to cropland). Table 7-2 presents the methodologies for each source and indicates their section.

Table 7-2. Overview of Land-Use Change Sources, Methods, and Sections

Section	Source	Proposed Method
7.2.1	Annual change in carbon stocks in biomass due to land conversion	The change in carbon stocks in biomass due to land conversion is estimated as the difference in carbon stocks in the current and previous land-use categories applied in the year of the conversion (carbon losses) or distributed uniformly over the transition period (carbon gains) (Aalde et al., 2006).
7.2.1	Annual change in carbon stocks in dead wood and litter due to land conversion	The change in carbon stocks in dead wood and litter due to land conversion is estimated as the difference in carbon stocks in the current and previous land-use categories applied in the year of the conversion (carbon losses) or distributed uniformly over the transition period (carbon gains) (Aalde et al., 2006).
7.2.3	Change in SOC stocks for mineral soils	The methodologies to estimate soil carbon stock changes for organic soils and mineral soils are adopted from methods created by the Intergovernmental Panel on Climate Change, or IPCC (Ogle et al., 2019a).

7.2 Estimation Methods

The methods provided in this chapter are strictly for portions of an entity's operation that have undergone a land-use change during the 20 years before the reporting year. The reporting convention is that all carbon stock changes associated with a land-use change are reported in the new land-use category. For example, in the case of conversion of forest land to cropland, both the initial carbon stock changes associated with the clearing of the forest and any subsequent carbon stock changes that result after the conversion are reported under cropland for 20 years following the conversion (IPCC, 2006).

As shown in equation 7-1, the change in C stocks associated with land-use change on a land parcel is the sum of the carbon stock changes in the individual pools, including biomass, DOM, and SOC.

Equation 7-1: Annual Carbon Stock Changes for a Land-Use Change as a Sum of Changes in Each Carbon Pool

$$\Delta C_{LUC_{PQ}} = (\Delta C_{Biomass_{PQ}} + \Delta C_{DOM_{PQ}} + \Delta C_{SOC_{PQ}}) \times CO_2MW$$

Where:

$\Delta C_{LUC_{PQ}}$	=	carbon stock changes for land-use change from previous land use P to current land use Q (metric tons CO_2-eq/year)
$\Delta C_{Biomass_{PQ}}$	=	annual change in biomass carbon stocks for land-use change from previous land use P to current land use Q (metric tons C/year)
$\Delta C_{DOM_{PQ}}$	=	annual change in carbon stocks in dead wood or litter for land-use change from previous land use P to current land use Q (metric tons C/year)
$\Delta C_{SOC_{PQ}}$	=	annual change in carbon stocks in soil organic carbon for land-use change from previous land use P to current land use Q (metric tons C/year)
CO_2MW	=	ratio of molecular weight of CO_2 to C = 44/12 (metric tons CO_2/metric tons C)
PQ	=	change from previous land use P to current land use Q (e.g., forest land converted to cropland, where forest land is the previous land-use category and cropland is the current land-use category)

In the case of conversion of forest land to cropland or grazing land, assess the carbon stock changes associated with each of the forest carbon pools plus harvested wood products.

7.2.1 Carbon Pools in Biomass

Method for Estimating Carbon Pools in Biomass

- The change in carbon stocks in live biomass due to land conversion is estimated as the difference in carbon stocks in the previous and current land-use categories applied in the year of the conversion (for biomass carbon losses) or distributed uniformly over the length of the transition period (for soil carbon stock changes and biomass carbon gains after the land use change).

7.2.1.1 Description of Method

Live biomass constitutes a significant carbon pool in many forests, and in some croplands and grazing lands. Following land-use conversion, use the sector-specific methods for estimating the biomass carbon stocks—detailed in the individual sector chapters—when estimating the previous and current biomass C stocks.

Equation 7-2 provides the conceptual approach to estimating changes in carbon stocks in biomass carbon pools (adapted from Aalde et al., 2006). Estimate the difference in biomass carbon stocks in the previous and current land use categories that occur at the time of the conversion ($\Delta C_{conversion}$), and also additional annual changes in biomass C stocks that occur in the current land use over the 20 years following conversion.

Equation 7-2: Annual Change in Carbon Stocks in Biomass Due to Land Conversion

$$\Delta C_{Biomass_{PQ}} = \left(\Delta C_{Biomass_{Q}} + \Delta C_{conversion_{PQ}}\right) \times A \div T$$

Where:

$\Delta C_{Biomass_{PQ}}$ = annual change in biomass carbon stocks for land-use change from land use P to land use Q (metric tons C/year)

$\Delta C_{Biomass_{Q}}$ = annual change in biomass carbon stocks for the current land use Q, which are based on the specific methods for the land use in other chapters of this report (metric tons C/ha)

$\Delta C_{conversion_{PQ}}$ = initial change in biomass carbon stocks due to conversion from previous land use P to current land use Q (metric tons C/ha)

A = area of the land parcel (ha)

T = time period of this estimation, which is 1 year for this equation (year)

PQ = change from previous land use P to current land use Q (e.g., forest land converted to cropland, where forest land is the previous land-use category and cropland is the current land-use category)

Q = current land use category

Note: $\Delta C_{conversion_{PQ}}$ is set to 0 after the first year following the conversion.

The initial change in biomass C stocks that occurs during the year of the conversion is estimated using equation 7-3 and addresses any biomass that stays on the land during the land-use conversion; for example, when forest is converted to grasslands, some trees may be left to provide shade for grazing livestock.

Equation 7-3: Initial Change in Biomass Carbon Stocks Due to Land Conversion

$$\Delta C_{conversion_{PQ}} = B_{After} - B_{Before}$$

Where:

$\Delta C_{conversion_{PQ}}$	=	initial change in biomass C stocks due to conversion of the previous land use to the current land use (metric tons C/ha)
B_{After}	=	biomass C stock remaining from the previous land use P after conversion (metric tons C/ha)
B_{Before}	=	biomass C stock in the previous land use P before the land-use conversion (metric tons C/ha)
PQ	=	change from previous land use P to current land use Q (e.g., forest land converted to cropland, where forest land is the previous land-use category and cropland is the current land-use category)

The change in biomass C stocks for the new land-use change category Q following conversion are estimated with equations found in the other chapters of this report. Notably, the change associated with harvested woody products has not been included here but may be estimated with methods outlined in chapter 5, associated with clearing/harvest of the forest biomass.

7.2.2 Carbon Pools in Dead Organic Matter

Method for Estimating Carbon Pools in Dead Organic Matter

- The change in carbon stocks in dead wood and litter due to land conversion is estimated as the difference in carbon stocks in the previous and current land-use categories applied in the year of the conversion (carbon losses) or distributed uniformly over the length of the transition period (carbon gains).

7.2.2.1 Description of Method

Equation 7-4 provides the conceptual approach to estimating changes in carbon stocks in dead wood and litter pools. Estimate the difference in carbon stocks in the previous and current land-use categories, then apply this change in the year of the conversion (i.e., there is a net loss in carbon stocks with conversion from land use P to land use Q) or distribute it uniformly over the length of the 20-year transition period (i.e., there is a gain in carbon stocks with conversion from land use P to land use Q).

Equation 7-4: Annual Change in Carbon Stocks in Dead Wood and Litter Due to Land Conversion

$$\Delta C_{DOM_{PQ}} = \left(C_{DOM_Q} - C_{DOM_P}\right) \times A \div T$$

Where:

$\Delta C_{DOM_{PQ}}$	=	annual change in carbon stocks in dead wood or litter for a land use change from previous category P to current category Q (metric tons C/year)
C_{DOM_Q}	=	dead wood/litter stock, under the current land-use category Q (metric tons C/ha)
C_{DOM_P}	=	dead wood/litter stock, under the previous land-use category P (metric tons C/ha)
A	=	area of the land parcel (ha)
T	=	time period of this estimation; the default is 20 years for carbon stock increases and one year for carbon losses (year)
PQ	=	change from previous land use P to current land use Q (e.g., forest land converted to cropland, where forest land is the previous land-use category and cropland is the current land-use category)

7.2.3 Changes in Soil Carbon

Method for Estimating Changes in Soil Carbon

- The methodologies to estimate soil carbon stock changes for organic soils and mineral soils are adopted from IPCC (Aalde et al., 2006, Ogle et al., 2019a).

SOC stocks are influenced by land-use change (Aalde et al., 2006) due to changes in productivity that influence carbon inputs, as well as changes in soil management that influence carbon outputs (Davidson and Ackerman, 1993; Ogle et al., 2005; Post and Kwon, 2000). For all land-use changes—and especially conversion to croplands—the most significant changes in SOC are due to changes in the soil disturbance regimes and associated effects on soil aggregate dynamics (Six et al., 2000).

While estimates should be made separately for each parcel of land that undergoes a change in land use, the stock changes will only be reported as a land-use change effect for a 20-year transition period, as noted above. For time series consistency, the method described in this section should be applied for the entire 20-year transition period to eliminate errors associated with changing the methods (i.e., changes in the stock due to a method changes rather than the anthropogenic activity).

7.2.3.1 Description of Method

Models have been adopted from the IPCC methods to estimate SOC stock change (Aalde et al., 2006, Ogle et al., 2019a). For mineral soils, use equation 7-6 to estimate carbon stocks at the beginning and end of the year. Emissions occur in organic soils following drainage due to the conversion of an anaerobic environment with a high-water table to aerobic conditions (Armentano and Menges, 1986), resulting in a significant loss of carbon to the atmosphere (Ogle et al., 2003). Emission estimation methods from organic soils should be consistent with the appropriate sector methodologies (i.e., forestry, croplands, grazing lands, or wetlands).

The total change in SOC stocks is estimated by summing the change in mineral and organic soils for the entity using equation 7-5.

Equation 7-5: Annual Change in SOC Stocks Due to Land Conversion

$$\Delta C_{SOC_{PQ}} = \Delta C_{mineral\,PQ} + \Delta C_{organic_{PQ}}$$

Where:

$\Delta C_{SOC_{PQ}}$	=	annual change in carbon stocks in soil organic carbon for land-use change from previous land use P to current land use Q (metric tons C/year)
$\Delta C_{mineral\,PQ}$	=	annual change in mineral soil organic carbon stock for land-use change from previous land use P to current land use Q (metric tons C/year)
$\Delta C_{organic_{PQ}}$	=	annual change in carbon stocks from drained organic soils for land-use change from previous land use P to current land use Q (metric tons C/year)
PQ	=	change from previous land use P to current land use Q (e.g., forest land converted to cropland, where forest land is the previous land-use category and cropland is the current land-use category)

Mineral Soils

The methods for estimating changes in SOC stocks for mineral soils has been adopted from the IPCC method (Ogle et al., 2019a). Estimate the change separately for each parcel in the entity's operation that has a land-use change. Use equation 7-6 (same as equation 3-8) to estimate the change in stocks for each area over 20-year intervals for the entire reporting time series.

Equation 7-6: Change in SOC Stocks for Mineral Soils Due to Land Conversion

$$\Delta C_{mineral\,PQ} = \left[\left(SOC_Q - SOC_P\right) \div t\right] \times A$$

Where:

$\Delta C_{mineral\,PQ}$	=	annual change in mineral soil organic carbon stock for land-use change from previous land use P to current land use Q (metric tons C/year)
SOC_Q	=	mineral soil organic carbon stock for the current land use Q (metric tons C/ha)
SOC_P	=	mineral soil organic carbon stock for the previous land use P (metric tons C/ha)
t	=	time period over which the land use, management and input factors quantify the change in SOC stocks, which is 20 years for this equation (year)
A	=	area of the parcel (ha)
PQ	=	change from previous land use P to current land use Q (e.g., forest land converted to cropland, where forest land is the previous land-use category and cropland is the current land-use category)

Estimate the SOC stock with country-specific factors using equation 3-8 from Chapter 3, copied here as equation 7-7.

Equation 7-7: SOC Stock for Mineral Soils

$$SOC = SOC_{ref} \times F_{LU} \times F_{MG} \times F_I$$

Where:

SOC	=	soil organic carbon stock on mineral soils for land use P or Q (metric tons C/ha)

SOC_{ref}	=	reference SOC stocks for United States agricultural lands in long-term cultivation (metric tons C/ha)
F_{LU}	=	stock change factor for land use (dimensionless)
F_{MG}	=	stock change factor for management regime (dimensionless)
F_I	=	stock change factor for the input of organic matter (dimensionless)

The stock change factors (F_{LU}, F_{MG}, F_I) and reference carbon stocks (SOC_{REF}) are country-specific values developed for the United States (Ogle et al., 2003, 2006). The reference stocks are based on the SOC stocks in croplands (table 7-3), while the land-use factors represent the relative change in SOC between cropland and grazing lands, forest land, and set-aside cropland (table 7-4). The management factors represent the influence of tillage in croplands and grassland conditions in grazing lands. The input factors represent the influence of changing plant productivity on carbon input to soils. Management and input factors are not needed for forest lands (i.e., factors are set to a value of one). See section 3.2.3.1 for more information about the classification of management and input for cropland and grazing lands.

Table 7-3. Reference Carbon Stocks and 95-Percent Confidence Intervals for the United States (Metric Tons C/ha)

IPCC Soil Categories	USDA Taxonomic Soil Orders	Cold Temperate, Dry	Cold Temperate, Moist	Warm Temperate, Dry	Warm Temperate, Moist	Sub-Tropical, Dry	Sub-Tropical, Moist
High-clay-activity mineral soils	Vertisols, Mollisols, Inceptisols, Aridisols, and high-base-status Alfisols	42 (±2.7)	65 (±2.2)	37 (±2.2)	51 (±2.0)	42 (±5.1)	57 (±25.5)
Low-clay-activity mineral soils	Ultisols, Oxisols, acidic Alfisols, and many Entisols	45 (±5.9)	52 (±4.5)	25 (±2.7)	40 (±2.4)	39 (±9.4)	47 (±27.2)
Sandy soils	Any soils with greater than 70% sand and less than 8% clay (often Entisols)	24 (±9.4)	40 (±7.3)	16 (±4.7)	30 (±3.9)	33 (±3.7)	50 (±15.5)
Volcanic soils	Andisols	124 (±22.3)	114 (±32.7)	124 (±22.3)	124 (±22.3)	124 (±22.3)	128 (±29.4)
Spodic soils	Spodosols	86 (±12.7)	74 (±13.3)	86 (±12.7)	107 (±16.3)	86 (±12.7)	86 (±12.7)
Aquic soils	Soils with aquic suborder	86 (±22.3)	89 (±7.1)	48 (±7.1)	51 (±3.5)	63 (±3.7)	48 (±16.5)

Source: Inventory Annex Table A-203, U.S. EPA, 2020.

Stocks represent the amount of SOC with long-term cultivation of the land parcel. The values in parentheses are 95-percent confidence intervals based on a normal distribution that can be used to quantify uncertainty and propagate error through the analysis.

Table 7-4. Land-Use, Management, and Input Factors and 95-Percent Confidence Intervals for the United States

Factor	Subtropical Moist and Warm Moist Climate	Subtropical Dry and Warm Dry Climate	Cool Moist Climate	Cool Dry Climate
Land-Use Factors				
Cultivated[a]	1	1	1	1
Wetland rice production factor[b]	2.14±0.13	2.14±0.13	1.85±0.15	1.85±0.15
General uncultivated (i.e., grazing land, forest land, wetlands, perennial crops)	1.58±0.12	1.58±0.12	1.37±0.15	1.37±0.1
Set-asides (e.g., Conservation Reserve Program Lands)	1.18±0.19	1.18±0.19	1.05±0.24	1.05±0.24
Cropland Management Factors				
Full intensive till[a]	1	1	1	1
Reduced till	1.05±0.08	1.00±0.09	1.05±0.08	1.00±0.09
No-till	1.14±0.06	1.09±0.07	1.14±0.06	1.09±0.07
Grazing Land Management Factors[c]				
Native or nominally managed grazing lands[a]	1	1	1	1
Moderately degraded from high-intensity grazing	0.90±0.14	0.90±0.14	0.90±0.14	0.90±0.14
Severely degraded from high-intensity grazing	0.70±0.55	0.70±0.55	0.70±0.55	0.70±0.55
Improved	1.14±0.25	1.14±0.25	1.14±0.25	1.14±0.25
Cropland Input Factors				
Low	0.94±0.02	0.94±0.02	0.94±0.02	0.94±0.02
Medium[a]	1	1	1	1
High	1.07±0.04	1.07±0.04	1.07±0.04	1.07±0.04
High with amendment[c]	1.44±0.19	1.37±0.16	1.44±0.13	1.37±0.16
Grazing Land Input Factors				
Improved with medium input[a]	1	1	1	1
Improved with high input[c]	1.11±0.15	1.11±0.15	1.11±0.15	1.11±0.15

Source: U.S. EPA, 2020.

[a] Uncertainty is not applicable because the uncertainty is already incorporated into the reference carbon stock.

[b] United States-specific factors are not estimated for wetland rice production due to a lack of studies addressing the impacts of wetland rice production on soil organic carbon stocks in the United States. Factors provided by IPCC for the Tier 1 method (Ogle et al., 2019b) are used as the best estimates of these impacts. USDA derived this factor by combining the land-use change factor for general uncultivated cropland (in this table) and the rice cultivation factor from the IPCC guidelines.

[c] United States-specific factors are not estimated for high input with an organic amendment for croplands, or grazing land management, due to a lack of studies addressing the impacts in the United States. Factors provided by IPCC for the Tier 1 method (Ogle et al., 2019b; McConkey et al., 2019) are used as the best estimates of these impacts.

The influence of biochar carbon amendments may also be included in the estimation of mineral SOC stock changes. Use the approach described in section 3.2.3.1 (equation 3-10).

Organic Soils

The methodology for estimating soil carbon stock changes in organic soils has been adopted from IPCC (Aalde et al., 2006; Ogle et al., 2019a) and is described accordingly in chapter 3 (equation 3-12) and copied here as equation 7-8. Chapter 5 recommends soil sampling in cases where there have been significant changes in soil carbon (e.g., land conversion). See for example, the "Level 3" approach for silvicultural practices and improved forest management in section 5.2.1 of chapter 5.

Equation 7-8: Change in SOC Stocks for Organic Soils

$$\Delta C_{organic_{PQ}} = A \times EF$$

Where:

$\Delta C_{organic_{PQ}}$	=	annual change in carbon stocks from drained organic soils in crop and grazing lands (metric tons C/ year)
A	=	area of drained organic soils (ha)
EF	=	annual emission factor (metric tons C/ha)
PQ	=	change from previous land use P to current land use Q (e.g., forest land converted to cropland, where forest land is the previous land-use category and cropland is the current land-use category)

Emission factors have been adopted from the U.S. National GHG Inventory (U.S. EPA, 2020; Ogle et al., 2003) and are region-specific and based on typical drainage patterns and climatic controls on decomposition rates.

Table 7-5. Emission Factors and 95-Percent Confidence Intervals for Organic Soils (i.e., *Histosols*) That Are Drained in Cropland and Grazing Land in the United States

Emission Factor for Drained Organic Soils (metric tons C/ha)	Cool Temperate Climate	Warm Temperate Climate	Subtropical Climate
Cropland	11.2 (±2.5)	14.0 (±2.5)	14.3 (±6.5)
Grazing land	2.8 (±1.3)	3.5 (±1.3)	3.6 (±3.3)

7.2.3.2 Activity Data

Mineral soils require the following activity for croplands:

- Area of land parcel (i.e., field)
- Crop types and rotation sequence
- Residue management, including harvested, burned, grazed, or left in the field
- Mineral fertilization (yes/no)
- Organic amendments (yes/no)

- Tillage implements and number of passes in each operation[1]
- Use of irrigation (yes/no)
- Cover crops (yes/no)

The method for grazing land on mineral soils requires the following management activity data:

- Area of the land parcel (i.e., field)
- Forage type (perennial grass such as cool or warm season grasses, legume, or mixed grass-legume nitrogen-fixing species)
- Mineral fertilization (yes/no)
- Organic amendments (yes/no)
- Use of irrigation (yes/no)
- Current ecological site and the reference condition for the land parcel based on the USDA, Natural Resources Conservation Service (NRCS) ecological state and transition model framework. The reference and alternative states are available through the USDA, NRCS web soil survey[2] (https://websoilsurvey.nrcs.usda.gov/app/).

The activity data are used to classify land-use, management, and input classes. The classifications can be found in chapter 3. Note that the method does not require any management activity data for forest land and wetlands because the method provided here assumes limited influence of forest or wetland management on SOC stock changes (i.e., the land-use change has the largest impact).

The method for organic soils requires the following activity data.

- Area of drained organic soils on the land parcel

7.2.3.3 Ancillary Data

Ancillary data include climate regions and soil types, consistent with the method developed by IPCC (Reddy et al., 2019). Weather data may be based on national datasets such as the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) data (PRISM Climate Group, 2018) and are classified according to the IPCC classification as refined for the United States (table 7-6). Soil data may also be based on national datasets such as the Soil Survey Geographic Database (SSURGO) (Soil Survey Staff, 2019), and are classified according to the IPCC classification (Reddy et al., 2019, Figure 3A.5.3). However, entities may also substitute field-specific soil data, as long as entities characterize the soil pedons necessary for use of the IPCC classifications. These characteristics include sand and clay content, soil order, and suborder (See table 7-3).

[1] Use this information to determine tillage intensity (i.e., intensive till, reduced till, and no-till), using the classification applied in the U.S. National GHG Inventory. See section 3.2.3.2 in chapter 3 for more information about the tillage classification.

[2] If the information is not available through the USDA-NRCS web soil survey, then the entity should contact USDA-NRCS extension office for guidance on identifying the current and reference conditions.

Table 7-6. Climate Classification for the SOC Methods Associated With Land-Use Change

Climate Type	Mean Annual Temperature (°C)	Mean Annual Precipitation (mm)
Cool temperate dry	<10	<Potential evapotranspiration
Cool temperate moist	<10	≥Potential evapotranspiration
Warm temperate dry	10–20	<Potential evapotranspiration
Warm temperate moist	10–20	≥Potential evapotranspiration
Subtropical dry	>20	<1,000
Subtropical moist	>20	1,000–2,000

Source: Reddy et al. (2019), Figure 3A.5.2

7.2.3.4 Limitations and Uncertainty

The limitations of the mineral SOC method include no assessment of the effect of land-use change at deeper depths in the profile (the IPCC method only addresses changes in the top 30 centimeters of the soil profile; Ogle et al. 2019a; Aalde et al., 2006), and no assessment of erosion, transport, and deposition ofcarbon. Uncertainties in the mineral soil methods include imprecision in the emission factors, in addition to uncertainties in the activity and ancillary data. Uncertainty for the emission factors is provided in chapter 3 (Ogle et al., 2003, 2006). Uncertainty in the activity data is based on the entity input, as well as the ancillary data to the extent that this information is provided by the entity. Uncertainties can be combined using a Monte Carlo simulation approach; see chapter 8.

While there is considerable evidence and mechanistic understanding about the influence of land-use change on SOC, there is less known about the effect on soil inorganic carbon. Consequently, current methods do not include impacts on inorganic carbon uncertainty associated with estimates of land use and management impacts on soil carbon stocks.

7.3 Chapter 7 References

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Appendix 7-A: Method Documentation

7-A.1 Rationale for Methods

These methods are based on the IPCC 2006 (Aalde et al., 2006) and refined in the 2019 Guidelines (Ogle et al., 2019a) and represent the most consistent way to estimate emissions from land-use change. Other methods are provided for land parcels that are not undergoing land-use change, and those methods are more comprehensive for estimating emissions for the specific land use. However, it is critical to use a consistent, seamless method for estimating carbon stock changes for an individual land parcel throughout the time series. Otherwise, artificial changes in stocks can be estimated due to a change in the method. Further testing and development will be needed before the more comprehensive methods provided in each land-use section can be integrated into a seamless approach for estimating the carbon stock changes.

Chapter 8
Uncertainty Quantification for Entity-Scale Greenhouse Gas Emissions

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Acronyms, Chemical Formulae, and Units

CO_2	carbon dioxide
dbh	diameter at breast height
GHG	greenhouse gas
LME	linear mixed effect
MVN	multivariate normal
N_2O	nitrous oxide
PDF	probability density function
PSU	primary sampling unit
UQ	uncertainty quantification

8. Uncertainty Quantification for Entity-Scale Greenhouse Gas Emissions

8.1 Introduction

This chapter provides an overview of options to quantify uncertainty for the emissions estimation methods provided in previous chapters of this report.

8.1.1 Overview of Methods for Predicting GHG Emissions

If greenhouse gas (GHG) emissions were measured at the entity scale, the only uncertainty would be due to the measurement process. But, in nearly all cases, the emissions are instead estimated by calculation methods. These methods vary in complexity, but all are functions of activity data inputs and emission factors.

- The simplest way to predict a GHG emission would be to multiply a known entity-scale activity data input by an entity-scale emission factor or set of factors. This is possible with some methods in this report; in those cases, the uncertainty in emission factors can be quantified and is provided in the description of the method. Examples include liming and carbon dioxide (CO_2) emissions, indirect soil nitrous oxide (N_2O) emissions, and non-CO_2 emissions from field burning of agricultural residues.
- The most complex methods described in this report involve models with many parameters that represent biogeochemical processes; for these methods, it is not feasible to derive uncertainty in the individual parameters. Uncertainty is instead quantified based on comparisons of model-based predictions to field measurements. Examples include cropland and grassland soil carbon stock changes and direct soil N_2O emissions, which are predicted with the DayCent ecosystem model.

Uncertainty quantification (UQ) in entity-scale GHG prediction is the formal process of describing the likelihood of different possible emissions, given what is known and what is unknown at the entity scale. In this report, the activity data inputs are assumed to be known, without uncertainty, at the entity scale based on the operator's knowledge about management of the system (i.e., assumed to be certain). Extensions to unknown activity data inputs are briefly discussed in section 8.4 for cases where the operator is not sure about the management activity.

Though activity data inputs are typically known without uncertainty at the entity scale, GHG emissions remain uncertain because they are not measured, and because they are determined by many factors that the prediction method does not fully capture. For example, suppose activity is measured by the size of a herd of cows. But cows naturally vary in their physiology due to breed, gender, age, and other factors, and this variation is affected by management practices and environmental factors (e.g., weather, pasture, or range conditions). Unless all these effects are incorporated into a perfect scientific model, the GHG emissions from this herd remain uncertain. In general, uncertainty in this report arises from uncertain emission factors: that is, it arises because the methods do not address all the relevant, naturally varying effects that determine the conversion of entity-scale activity to GHG emissions.

In this report, uncertainty in GHG emissions is quantified via a probability density function (PDF), described in further detail in section 8.2.2. Uncertainty in the emission factors, which is also based on PDFs for the factors, needs to be propagated through the method to determine the final PDF of

GHG emissions for the entity. One standard approach for propagating uncertainty is a Monte Carlo analysis, described in section 8.2.3.

8.1.2 Decision Tree for Classifying Emission Source Methods for UQ

The complexity of the Monte Carlo analysis for propagation of uncertainty is determined in large part by the method. Figure 8-1 presents two ways methods are classified in this report.

First, methods are either model-based or measurement-based:

- For **model-based** methods, uncertainty at the entity scale is fully described by PDFs for emission factors (available elsewhere in this report), with no entity-scale measurements required to determine the PDF. Examples of model-based methods include liming and urea CO_2, soil N_2O and soil carbon methods.
- In **measurement-based** methods, PDFs for emission factors and parameters are estimated from measurements at the entity scale (typically from a sample), and the resulting PDFs introduce uncertainty into the emissions estimate. As an example, a random sample of trees on a woodlot could have its volume characteristics measured to represent the entire woodlot and the growth over time, resulting in a PDF as described in the methods for woody biomass carbon stocks for cropland and grazing land.

Second, model-based methods are either implicit or explicit:

- **"Implicit"** means there is no PDF directly on model parameters, possibly due to the number of parameters or the complexity of the model. (It is theoretically possible to quantify the uncertainty in parameters for a complex model as a joint probability distribution, which would then be classified as an explicit method, but this is not the case for the complex methods included in this report). Implicit methods rely on an empirical method (a statistical model) for comparing measurements to model outputs. The implicit method should also control independent variables (covariates), that may explain some of the uncertainty in GHG emissions, and correlations (e.g., spatial autocorrelation), induced by the design of the studies performed to obtain the measurements. Examples of implicit methods include soil carbon stock changes and direct soil N_2O emissions, which are predicted with the DayCent ecosystem model.
- For **explicit** methods, PDFs are derived directly on parameters, which are typically emission factors; for those cases, this report provides the PDFs with each source category. Explicit methods usually have relatively few parameters and relatively simple model structure. Examples include liming and CO_2 emissions, indirect soil N_2O emissions, and non-CO_2 emissions from field burning of agricultural residues.

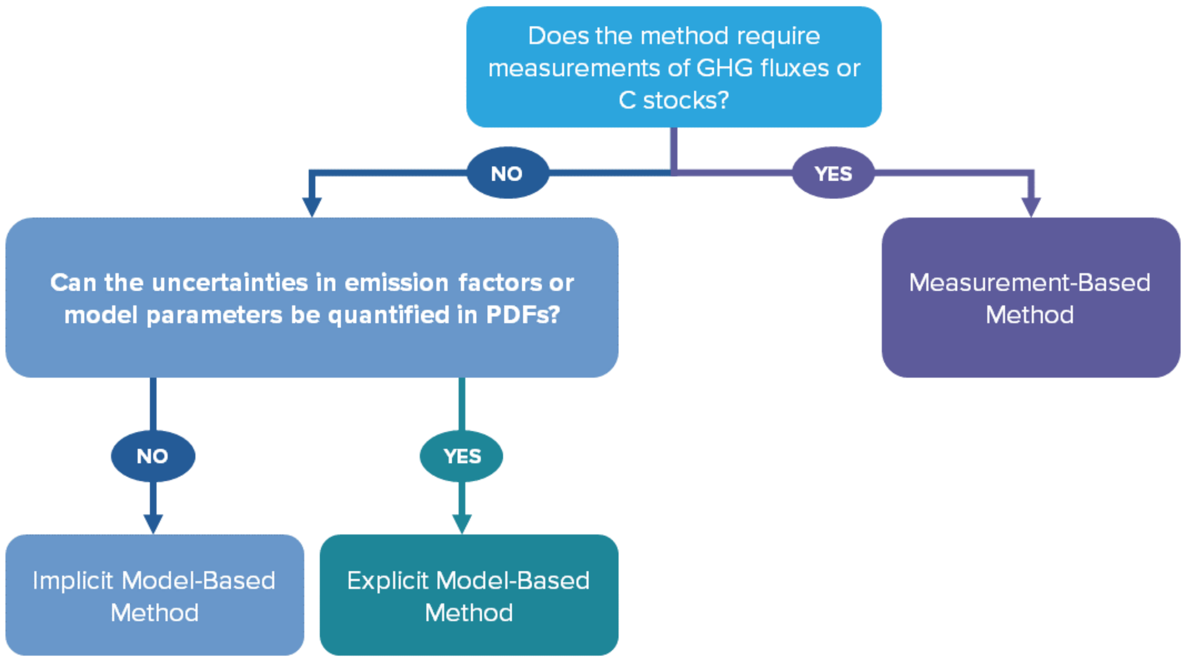

Figure 8-1. Decision Tree to Choose the Type of Method for a Source Category (See Section 8.3 for Error Propagation Methods for Each Type)

8.1.3 Organization of the Chapter

- Section 8.2 gives an overview of UQ, including general principles for describing uncertainty via PDFs, propagating uncertainty via Monte Carlo methods, summarizing Monte Carlo output, and interpreting the summaries.
- Section 8.3 provides step-by-step guidance for UQ with explicit model-based methods (section 8.3.1), explicit measurement-based methods (section 8.3.2), and implicit model-based methods (section 8.3.3).
- Section 8.4 describes extensions of the Monte Carlo analysis for unknown activity data inputs.

8.2 Overview of UQ

8.2.1 Sources of Uncertainty in Entity-Scale GHG Prediction

Suppose $\mu(a, f)$ is the true entity-scale GHG emission given known activity data inputs a and known emission factors f. Let $m(A, F)$ denote the GHG prediction method output for uncertain activity data inputs A and unknown emission factors F. Then the difference between the prediction from the method using these unknown inputs and the true GHG emission can be written as

$$m(A, F) - \mu(a, f) = \{m(A, F) - m(a, F)\} + \{m(a, F) - m(a, f)\} + \{m(a, f) - \mu(a, f)\}.$$

- The first term, $m(A, F) - m(a, F)$, is due to unknown activity data inputs and is assumed to be zero in this report. (See section 8.4.)
- The second term, $m(a, F) - m(a, f)$, is due to uncertain emission factors, the dominant source of uncertainty for most sources in this report. Uncertainty due to uncertain emission

factors is quantified by creating PDFs and using Monte Carlo analysis to propagate the uncertainty through the method to the GHG emission.

- The last term, $m(a, f) - \mu(a, f)$, is model uncertainty due to misspecification (e.g., incompleteness) of the scientific model. In this report, the explicit methods focus only on the dominant sources of uncertainty given current scientific understanding; they do not include model uncertainty. The implicit method does include model uncertainty, because it is an empirical method that compares model predictions to emissions observations.

8.2.2 UQ via PDFs

For this report, uncertainty in a generic quantity Y is described with a PDF $p_Y(y)$, which is a function that takes a possible value y of Y and returns a nonnegative "probability density." This probability density is not itself a probability, but the integral of the PDF over a specified interval of values from a to b is the probability that the random quantity Y takes on a value between a and b:

$$\mathrm{P}[a \leq Y \leq b] = \int_a^b p_Y\,(y)\,dy.$$

PDFs are provided for the emission factors and other calculation variables for some of the source categories, and PDFs for the emission estimates are generated using the UQ methods for the source categories.

A simple example of UQ for an explicit, model-based method that predicts GHG emissions as $G = m(A, F)$ would be $G = m(A, F) = A \times F$, where A represents one or more entity-level activity data inputs, and F represents one or more entity-level emission factors. The entity-level activity data are known ($A = a$ for some specified value(s), a). The entity-level emission factors are unknown, and their uncertainty is described by one or more given PDFs, $p_F(f)$, in the methods report. For simplicity, the report considers a single activity data input and emission factor.

Because the entity-level emissions depend on at least one unknown input, G is unknown and its uncertainty is described by a PDF, $p_G(g)$. This PDF for G is produced by "propagating" the uncertainty in the emission factor through the method. For this report, the error is propagated using a Monte Carlo approach, as discussed in section 8.2.3.

8.2.3 General Principle of Propagating Uncertainty Via Monte Carlo

Monte Carlo analysis is a principled and straightforward approach to uncertainty propagation. It generates a large number of replicates (e.g. 10,000 replicates) of the possible GHG emissions. This analysis is typically performed using statistical software. Random numbers are selected for the emission factors based on the PDF and used with the activity data to estimate GHG emissions. This process is replicated many times and then the GHG emissions PDF and its properties (e.g., mean, variance, and the median and other percentiles) are estimated using statistical techniques.

Figure 8-2 presents a generalized process, see sections 8.3.1 through 8.3.3 for specific steps based on this method.

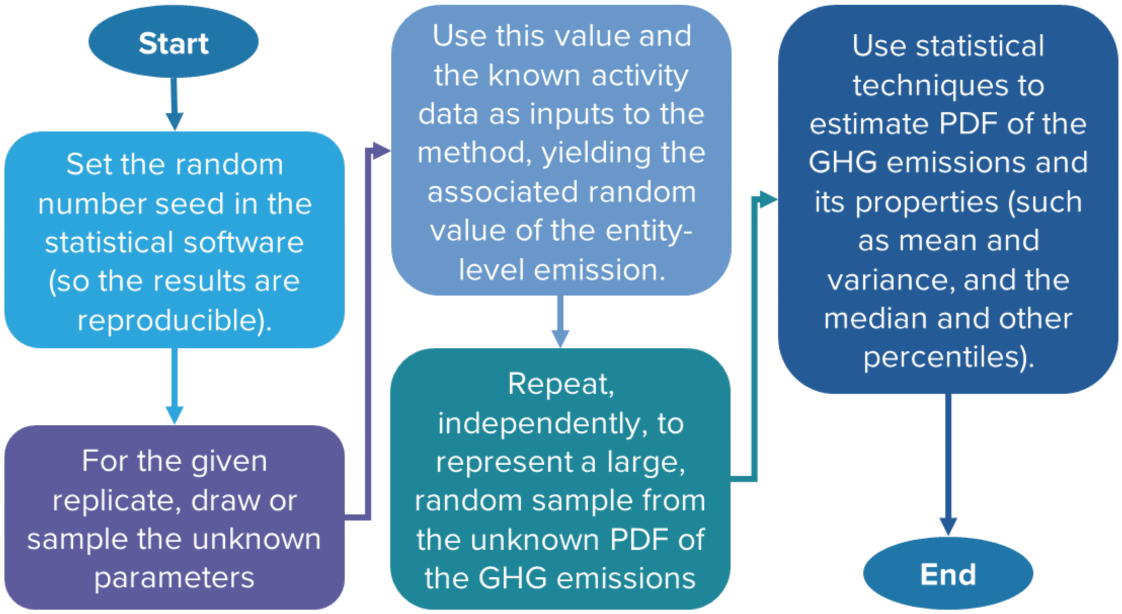

Figure 8-2. UQ via Monte Carlo Analysis

Because it relies on a random sample, the Monte Carlo analysis introduces a new source of uncertainty, which has nothing to do with the original uncertainty in GHG emissions. However, the Monte Carlo uncertainty can be made as small as desired in approximating the unknown PDF $p_G(g)$ because the sample size M can be made large, limited only by computing time.

Increasing M does not decrease the uncertainty about GHG emissions, but simply gives a more precise estimate of the PDF for the GHG emissions. Uncertainty about the entity-level GHG emissions would only be reduced by directly measuring entity-level GHG emissions, by measuring or otherwise reducing uncertainty about entity-level emission factors, or by improving the scientific model.

The Monte Carlo approach has several strengths. First, it is transparent because it does not involve complicated mathematical derivations. Second, it is readily transferable across methods, as it is a general-purpose approach, regardless of the complexity of the method. Third, it is easily adaptable as new information becomes available. For example, if a new source of uncertainty in the method is identified and its PDF is developed, or if the PDF is refined for a known source of uncertainty in the method, the Monte Carlo analysis is easily updated to reflect this new information.

The Monte Carlo approach can also be used to propagate uncertainty when emission predictions are summed across different sources, **provided the uncertainties in those predictions are independent.** For example, doing so would be reasonable if the underlying data used to derive the estimates are independent between source categories—and not reasonable if the underlying data are the same for source categories. Monte Carlo methods can be adapted to handle the uncertainty in sums of predictions across different sources that cannot be regarded as independent, but this is beyond the scope of this chapter.

8.2.4 Recommendations for Summarizing Monte Carlo Output

The following provides an overview of how to summarize Monte Carlo output. Note that statistical software typically provides Monte Carlo analyses summary plots and information.

1. Plot the Monte Carlo approximation to the PDF, either as a histogram of the data set $\{G_r\}_{r=1}^{M}$ or as a smoothed version of the histogram, via a kernel density estimator. Check that values along the horizontal axis are plausible values of entity-level GHG emissions, with higher density corresponding to more plausible values.
2. Estimate and report a central value of the GHG emissions PDF.

   While the mode, or most frequent value, is one standard measure of central tendency, it is not readily estimated by the Monte Carlo approach this report describes for UQ, and is not recommended for most PDFs encountered in GHG uncertainty computations. (The exception is right-triangular PDFs, described in section 8.2.6.)

   Another standard measure of central tendency is the mean. While the theoretical mean of the GHG emissions PDF is readily estimated by the empirical average of the Monte Carlo replicates, use the median. The theoretical median is defined for continuous $p_G(g)$ as the value $\theta_{0.5}$ such that:

   $$0.5 = \mathrm{P}[G \leq \theta_{0.5}] = \int_0^{\theta_{0.5}} p_G\,(g)\,dg;$$

   The median cuts off $0.5 \times 100\%$ of the probability in the PDF, so it is the 50th percentile. Other percentiles (2.5th and 97.5th) are used in determining a prediction interval for the GHG emissions from the entity, so choice of the median implies that a common set of estimation methods can be used to summarize the Monte Carlo results. Also, the median is insensitive to skewness and heavy tails, unlike the mean, and generally simple to understand.

   To estimate the median and other percentiles, first sort the Monte Carlo replicates to obtain the order statistics:

   $$G_{(1)} \leq G_{(2)} \leq \cdots \leq G_{(r)} \leq \cdots \leq G_{(M)},$$

   The parentheses in the subscripts denote sorted data. Then choose the value in the "middle" of the sorted list by picking the order statistic with index equal to ceiling$(0.5M)$: $\hat{\theta}_{0.5} = G_{(\mathrm{ceiling}(0.5M))}$. For example, choose $G_{(500)}$ if $M = 1{,}000$ or $G_{(501)}$ if $M = 1{,}001$.[1]

   The empirical median is the Monte Carlo estimate of the theoretical median, $\theta_{0.5}$. Similarly, other percentiles are defined as the values θ_q that cut off $q \times 100\%$ of the probability in the PDF,

   $$q = \mathrm{P}\big[G \leq \theta_q\big] = \int_0^{\theta_q} p_G\,(g)\,dg.$$

   To estimate each percentile, choose the corresponding empirical percentile: the qMth order statistic in the sorted list, rounding up if qM is not an integer:

[1] Another standard definition of the empirical median takes the unique middle value if M is odd and the average of the two middle values if M is even, but for the large values of M used in Monte Carlo analysis, this distinction is not important. This report uses the definition above for consistency with other percentiles.

$$\hat{\theta}_q = G_{(\text{ceiling}(qM))}.$$

3. Report estimates of the 2.5th and the 97.5th percentiles, because these theoretical quantities satisfy the following probability equation for the entity-level GHG:

$$0.95 = 0.975 - 0.025 = \mathrm{P}[G \le \theta_{0.975}] - \mathrm{P}[G \le \theta_{0.025}] = \mathrm{P}[\theta_{0.025} \le G \le \theta_{0.975}].$$

   Estimating the theoretical percentiles with the corresponding empirical percentiles,

$$(\hat{\theta}_{0.025}, \hat{\theta}_{0.975}) = \left(G_{(\text{ceiling}(0.025M))}, G_{(\text{ceiling}(0.975M))}\right),$$

   yields a Monte Carlo 95-percent prediction interval for the entity-level GHG. That is the probability that the true entity-level GHG emission G lies between $\hat{\theta}_{0.025}$ and $\hat{\theta}_{0.975}$ is approximately 0.95.

To summarize, (1) plot the Monte Carlo approximation to the PDF, typically as a histogram; (2) compute and report a measure of central tendency, i.e., the empirical median; then (3) compute and report an approximate 95-percent prediction interval by using the empirical 2.5th and 97.5th percentiles.

Box 8-1. Assessing the Precision of Monte Carlo Estimates

Because the empirical median and other percentiles are estimates from the Monte Carlo sample, they have their own uncertainties, which can be made smaller by increasing the Monte Carlo sample size, M. That is, if the Monte Carlo analysis were repeated, the estimated median and other estimated percentiles would change, due to the random sampling, but the amount of possible change will be small for a larger M. The amount of possible change in the estimated percentiles can be quantified from the same Monte Carlo sample used to estimate the percentiles, by computing 95-percent confidence intervals for the percentiles. These confidence intervals use standard statistical large-sample approximations, which are excellent for the large values of M in typical Monte Carlo analysis.

These confidence intervals would usually not be reported: they are used only by the analyst to assess the precision of the Monte Carlo estimates. If the intervals are deemed to be too wide, the Monte Carlo analysis would be expanded by increasing the value of M.

Theoretical percentiles θ_q are estimated via order statistics (empirical percentiles), $\hat{\theta}_q$, as described above. Confidence intervals for theoretical percentiles are obtained by choosing pairs of order statistics, as follows. First, choose the index of the lower order statistic, rounding down to get an integer:

$$L = \text{floor}\left\{0.5 + (Mq) - 1.96\sqrt{Mq(1-q)}\right\}.$$

Second, choose the index of the upper order statistic, rounding up to get an integer:

$$U = \text{ceiling}\left\{0.5 + (Mq) + 1.96\sqrt{Mq(1-q)}\right\}.$$

Finally, the confidence interval for the percentile θ_q is the pair of order statistics, $\left(G_{(L)}, G_{(U)}\right)$.

For example, consider the theoretical 2.5th percentile, $\theta_{0.025}$, and suppose $M = 10{,}000$. Then $Mq = 250$, so the empirical percentile is $\hat{\theta}_{0.025} = G_{(250)}$, and the indices for the confidence interval for $\theta_{0.025}$ are

$$L = \text{floor}\left\{0.5 + (10{,}000 \times 0.025) - 1.96\sqrt{10{,}000 \times 0.025(0.975)}\right\} = 219$$

and

$$U = \text{ceiling}\left\{0.5 + (10{,}000 \times 0.025) + 1.96\sqrt{10{,}000 \times 0.025(0.975)}\right\} = 282.$$

This translates to 95 percent confidence that the theoretical 2.5th percentile, $\theta_{0.025}$, lies between the order statistics $G_{(219)}$ and $G_{(282)}$ obtained in the Monte Carlo simulation with $M = 10{,}000$ replicates. If this interval is too wide for sufficient precision, simply increase the Monte Carlo sample size.

Similar computations can be conducted for the upper endpoint of the prediction interval, $\theta_{0.975}$, or for the median, $\theta_{0.5}$.

8.2.5 Numerical Example of Monte Carlo Analysis

To illustrate the Monte Carlo analysis, consider an example of an explicit, model-based method that predicts GHG emissions as $G = m(A, F) = A \times F$, with the activity data input known to be $A = 10$ and with the unknown emission factor F described by a normal PDF with theoretical mean, $\mu_F = 3$ and variance, $\sigma^2 = 1$:

$$p_F(f) = \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{1}{2}(f-3)^2\right\}.$$

For this example, the PDF of G is also normal, with theoretical median $\theta_{0.5} = 30$, theoretical 2.5th percentile $\theta_{0.025} = 10.4$, and theoretical 97.5th percentile $\theta_{0.975} = 49.6$ and the theoretical quantities estimated using 10,000 replications of the Monte Carlo analysis ($M = 10{,}000$). Random emission factors $F_1, F_2, \ldots, F_M$ drawn independently from the normal distribution with mean (3) and variance (1), help compute the simulated emissions ($G_1 = 10F_1, G_2 = 10F_2, \ldots, G_M = 10F_M$)

To summarize the Monte Carlo draws:

1. Plot the histogram, as shown in figure 8-3. In a Monte Carlo analysis, the true PDF of the GHG emissions (G) would be unknown, but it is known in this illustration and is plotted in the figure as a dashed, bell-shaped curve. The histogram is an excellent approximation to the true PDF.
2. Compute and report the empirical median as a measure of central tendency. For any Monte Carlo sample of size $M = 10{,}000$, the empirical median will be the order statistic with index equal to ceiling $(0.5M) = 5{,}000$. For the Monte Carlo simulation used in this illustration, the empirical median is

$$\hat{\theta}_{0.5} = G_{(5{,}000)} = 29.93,$$

   This is very close to the theoretical median $\theta_{0.5} = 30$. The theoretical median is plotted as a vertical dashed line and the empirical median is plotted as a vertical solid line in the center of figure 8-3. The two lines are nearly coincident and difficult to distinguish visually.
3. Compute and report a 95-percent prediction interval for G, using the empirical 2.5th percentile and the empirical 97.5th percentile:
4. Empirical 2.5th percentile $\hat{\theta}_{\text{ceiling}(0.025M)} = G_{(250)} = 10.37$.
5. Empirical 97.5th percentile $\hat{\theta}_{\text{ceiling}(0.975M)} = G_{(9{,}750)} = 49.37$.

6. Ninety-five percent of all GHG emissions are expected to fall between these bounds. These empirical bounds are close to the true theoretical percentiles of $\theta_{0.025} = 10.4$ and $\theta_{0.975} = 49.6$. The theoretical 2.5th percentile is plotted as a vertical dashed line and the empirical 2.5th percentile is plotted as a vertical solid line on the left of figure 8-3. The theoretical 97.5th percentile is plotted as a vertical dashed line and the empirical 97.5th percentile is plotted as a vertical solid line on the right of figure 8-3. In each case, the estimates and theoretical values are difficult to distinguish visually.

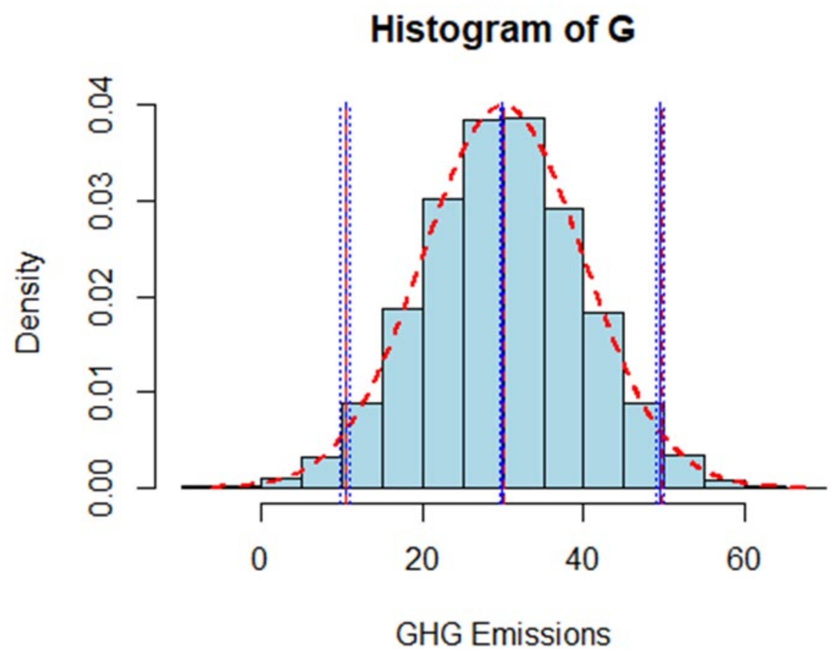

Figure 8-3. Histogram From M = 10,000 Monte Carlo Draws From a Normal Distribution (Curved Dashed Line), with True Percentiles Plus Estimates and Confidence Intervals

If the Monte Carlo analysis were repeated, the estimated median and 2.5th and 97.5th percentiles would change but would not change by much if M is large. To determine if $M$is large enough (e.g., 10,000 replications) use the Monte Carlo sample to compute 95-percent confidence intervals corresponding to each estimated percentile, as shown in box 8-1: the width of these confidence intervals gives an idea of expected variation if the Monte Carlo were repeated. If the intervals are sufficiently narrow, conclude that the Monte Carlo sample size is sufficient.

A 95-percent confidence interval for the median is the pair of order statistics with indices:

$$L = \text{floor}\{0.5 + (0.5M) - 1.96\sqrt{M(0.5)(0.5)}\} = 4{,}902$$

$$U = \text{ceiling}\{0.5 + (0.5M) + 1.96\sqrt{M(0.5)(0.5)}\} = 5{,}099.$$

The 95-percent confidence interval for the median from the Monte Carlo sample is:

$$\left(G_{(4{,}902)}, G_{(5{,}099)}\right) = (29.69{,}30.15),$$

This shows that the theoretical median is precisely estimated. The confidence interval is plotted with a pair of vertical dotted lines in the center of figure 8-3.

For the 2.5th percentile, the 95 percent confidence interval uses the indices $L = 219$ and $U = 282$, so the confidence interval is (9.77, 10.88). The confidence interval is plotted with a pair of vertical dotted lines on the left of figure 8-3.

For the 97.5th percentile, the confidence interval uses the indices $L = 9{,}719$ and $U = 9{,}782$, so the confidence interval is (48.99, 49.85). The confidence interval is plotted with a pair of vertical dotted lines on the right of figure 8-3.

The confidence intervals for the median and 2.5th and 97.5th percentiles show that with $M = 10{,}000$, each theoretical percentile is precisely estimated. If the intervals were judged to be insufficiently narrow, the Monte Carlo analysis could be repeated with a larger value of M.

Box 8-2. Potential Reduction in Uncertainty With Aggregation Across Entities

Uncertainties are often large at the entity scale, and carbon programs need ways to manage the risk associated with this uncertainty. Aggregation across entities is one way to reduce those uncertainties.

Consider the simplest version of an explicit GHG emissions model, in which the emissions are computed as $G_j = a_j F_j$, where $a_j > 0$ is the known activity data for entity j and F_j is the unknown emission factor for entity j. The uncertainty in the emission factor is reflected in a PDF with mean μ and variance σ^2. Important here is the coefficient of variation, defined as the standard deviation of emissions relative to expected emissions, in percent for the total emissions over n entities:

$$cv = \frac{\sqrt{\mathrm{Var}\left(\sum_{j=1}^{n} a_j\, F_j\right)}}{\mathrm{E}\left[\sum_{j=1}^{n} a_j\, F_j\right]} \times 100\%,$$

If $n = 1$, this expression becomes

$$cv = \frac{\sqrt{\mathrm{Var}(a_1 F_1)}}{\mathrm{E}[a_1 F_1]} \times 100\% = \frac{\sqrt{a_1^2 \sigma^2}}{a_1 \mu} \times 100\% = \frac{\sigma}{\mu} \times 100\%.$$

As n increases, the variance increases, but so does total emissions; therefore, relative uncertainty as measured by cv decreases. The amount of decrease depends on the amount of correlation among emission factors on different entities, $\mathrm{Corr}(F_j, F_k)$ for $j \neq k$.

Entity-level emission factors are unlikely to be identical due to natural variation from entity to entity. Nearby entities with similar geographic characteristics and similar management practices might be expected to have more similar emission factors, and hence higher correlation, than entities that are more “distant” in terms of entity-level conditions and practices. For simplicity, assume all the entities that are combined have the same amount of correlation with each other, $\mathrm{Corr}(F_j, F_k) = \rho$ for $j \neq k$. The most extreme versions of this assumption are $\rho = 1$, so that entities have perfectly correlated emission factors, and $\rho = 0$, so that entities have uncorrelated emission factors. The true correlations are likely to vary across pairs of entities, with some higher and some lower values.

Under the assumption of constant correlation, it can be shown that

$$cv = \frac{\sigma}{\mu}\left\{\rho + \frac{\left(\sum_{j=1}^{n} a_j^2\right)/n}{\left(\sum_{j=1}^{n} a_j/n\right)^2}\frac{(1-\rho)}{n}\right\}^{1/2} \times 100\%.$$

If $\rho = 1$, then the entities have perfectly correlated emission factors, and the relative uncertainty never decreases: it equals $(\sigma/\mu) \times 100\%$ for any number of entities. In all cases with $\rho \neq 1$, the relative uncertainty decreases as the number of entities in the sum increases, with the greatest decrease when the entities have uncorrelated emission factors.

Figure 8-4 shows the coefficient of variation as a function of ρ and number of entities, for a simulated example in which the activity data are simulated as normal random variables with mean 10 and standard deviation 1 and then treated as fixed and known, while the random emission factors have mean $\mu = 10$ and standard deviation $\sigma = 5$. The coefficient of variation for a single entity, or any number of perfectly correlated entities, is then $(\sigma/\mu) \times 100\% = 50\%$. For all other cases, the coefficient drops below 50%, with the greatest decrease when the entities' emission factors are uncorrelated.

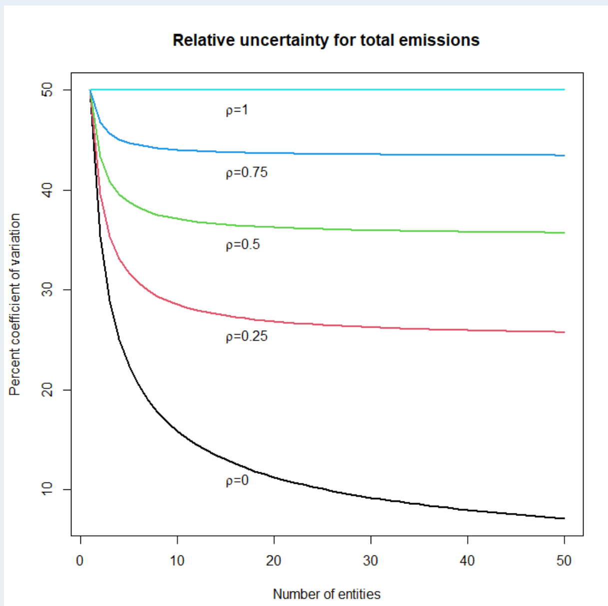

Figure 8-4. Relative Uncertainty for Total Emissions, Measured as Percent Coefficient of Variation, Decreases as the Number of Entities in the Sum Increases, Provided Those Entities Do Not Have Perfectly Correlated Emission Factors

8.2.6 Special Case: Right-Triangular Distribution

For some sources (e.g., urea CO_2), the uncertainty is described with a right-triangular PDF, which describes all possible values of the emission factor as lying between zero and some maximum value, ϕ, with PDF that increases linearly from zero at zero to $2/\phi$ at ϕ. Mathematically, the PDF is $p_F(f) = 2f/\phi^2$ for $0 \leq f \leq \phi$, otherwise $p_F(f) = 0$. If the GHG emission is $G = aF$ for some known activity data input, a, then the PDF of G can be derived directly, rather than via Monte Carlo. The resulting PDF is $p_G(g) = 2g/(a\phi)^2$ for $0 \leq g \leq a\phi$ and $p_G(g) = 0$ elsewhere. This PDF is shown in figure 8-5.

For this right-triangular PDF, the standard prediction approach is to use the mode, $a\phi$, instead of the mean or median. The Monte Carlo approach is not used to determine a prediction interval. Instead, the prediction interval is determined analytically as $(\sqrt{\alpha}a\phi, a\phi)$. The probability that the GHG emission falls in this interval is then the difference in area between the large triangle and the small triangle in figure 8-5, or $1 - \left(\frac{1}{2}\right)\left(\sqrt{\alpha}a\phi\right)\frac{2\sqrt{\alpha}}{a\phi} = 1 - \alpha$. For $\alpha = 0.05$, this yields a 95-percent prediction interval.

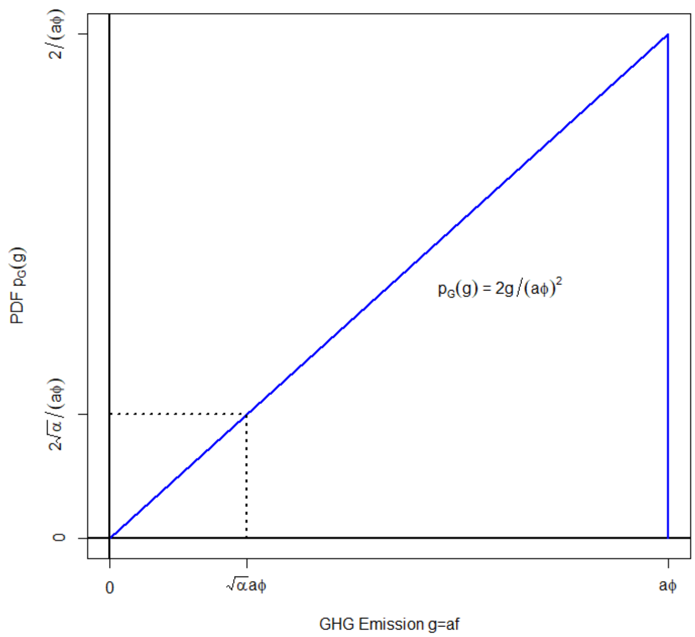

Figure 8-5. Right-Triangular PDF for GHG Emission With Known Activity, $\boldsymbol{a}$, and Lower Bound of $(1-\alpha)100\%$ Prediction Interval

8.3 Step-by-Step Guidance for UQ

8.3.1 Explicit Model-Based Methods

For explicit model-based methods, PDFs can be placed directly on parameters, which are typically emission factors, and no entity-scale measurements are needed to determine the relevant PDFs. Instead, these PDFs are provided in the methods description for each source. If these PDFs are not right-triangular, use a Monte Carlo approach as described in section 8.2.3:

1. Start by setting the random number seed in the statistical software, so that results are reproducible.
2. For the rth replicate, select a random draw F_r of the unknown emission factor(s) from the relevant PDFs. In models with multiple factors or parameters, select random draws from the joint probability distribution of the factors or parameters. For example, multiple factors or parameters that have a multivariate normal as their joint distribution will be specified in terms of a mean vector and a covariance matrix. If a joint probability distribution is not otherwise specified, then randomly select values from each of the PDFs for the factors or parameters. This selection implies that the factors or parameters are independent, and their joint distribution is the product of the individual PDFs.

3. Use these random values and the known activity data as inputs to the method, yielding the rth random value $G_r = m(a, F_r)$ of the entity-level emission.
4. Repeat, independently, for $r = 1,2, \dots, M$. The resulting M Monte Carlo replicates $\{G_r\}_{r=1}^{M}$ represent a large, random sample from the unknown PDF $p_G(g)$.
5. Summarize the Monte Carlo results based on the median and 95-percent prediction interval, as described in section 8.2.4.

8.3.2 Explicit Measurement-Based Methods

For measurement-based methods, this report does not directly provide PDFs for emission factors; they are instead estimated from measurements at the entity scale. Typically, these measurements are taken only on a sample, so some uncertainty is introduced. For example, a random sample of trees on a woodlot could have its volume characteristics measured to represent the entire woodlot and the growth over time, resulting in a PDF.

PDFs for these explicit measurement-based methods will be context-specific, but the general approach of Monte Carlo UQ will still apply. Because the unknown emission factor will typically rely on both model parameters estimated from sources outside the entity and entity-level measurements, denote the unknown emission factor by:

$$F = h(\theta, \kappa)$$

where:

$h()$	=	a known function
θ	=	one or more unknown model parameters that are estimated from scientific studies external to the entity
κ	=	one or more unknown entity-level characteristics

Because the model parameters are often estimated by regression or other statistical techniques, it is reasonable to treat the PDF for the unknown θ parameters as multivariate normal (MVN) with mean vector μ_θ and variance-covariance matrix Σ_θ. The estimates of μ_θ and Σ_θ are obtained from this methods document, using information from scientific studies that are independent of the entity.

In many cases, the unknown entity-level characteristics κ will be estimated based on measurements obtained from a sample. Standard probability sampling designs include all units in the population of interest in a “sampling frame” and have positive and known probabilities of selection. These sampling designs lead to approximately normally distributed estimates of κ in moderate to large sample sizes, under very mild conditions on the characteristics of the measurements. There is no need for the original measurements to be normal or close to normal: the measurements could be binary, or counts, or right-skewed continuous. It is therefore reasonable to treat the PDF for the unknown entity-level characteristics κ as MVN with mean vector μ_κ and variance-covariance matrix Σ_κ. The covariances in Σ_κ are usually not zero because estimated characteristics that use the same sample are correlated.

The estimates of μ_κ and Σ_κ are obtained from entity-level measurements and the sampling design that leads to the measurements. Methods of estimation for different designs are well-documented. Statistical software (including SAS, Stata, SPSS, and the “survey” package in R) can provide estimates of the mean vector and covariance matrix given basic information on the sampling design, including:

- Unique stratum identifiers (if any), which are disjoint subpopulations that cover the population and from which independent samples are selected;
- Unique identifiers of primary sampling units (PSUs) which are the units initially sampled from the frame, even if there are subsequent stages of selection; and
- Sampling weights, which are the inverses of the sample inclusion probabilities.

A complete description of estimation and variance estimation for various sampling designs is beyond the scope of this chapter.

In explicit model-based methods, the Monte Carlo analysis begins by sampling $F_1, F_2, \ldots, F_M$ independently from a given PDF, $p_F(f)$. For the explicit measurement-based methods of this section, use a Monte Carlo analysis as described in section 8.2.3. See box 8-3 for a sample calculation:

1. Start by setting the random number seed in the statistical software, so that results are reproducible.
2. For the rth replicate, sample θ_r independently from $\mathrm{MVN}(\mu_\theta, \Sigma_\theta)$, sample κ_r independently from $\mathrm{MVN}(\mu_\kappa, \Sigma_\kappa)$, and compute $F_r = h(\theta_r, \kappa_r)$.
3. Use these random values and the known activity data as inputs to the method, yielding the rth random value $G_r = m(a, F_r)$ of the entity-level emission.
4. Repeat, independently, for $r = 1,2, \ldots, M$. The resulting M Monte Carlo replicates $\{G_r\}_{r=1}^{M}$ represent a large, random sample from the unknown PDF $p_G(g)$.
5. Summarize the Monte Carlo results based on the median and 95-percent prediction interval, as described in section 8.2.4.

Box 8-3. Example of Explicit Measurement-based Method

Equation 3-6 (in chapter 3) describes aboveground woody tree biomass stock, a key determinant of the unknown emission factor, as:

$$h(\theta, \kappa) = \{\beta_0(average\ stems\ per\ plot) + \beta_1(average\ \ln(dbh)\}(\#plots\ per\ ha)(area\ in\ ha)$$

Table 3-6 (in chapter 3, provided with relevant entries below) presents $\theta \quad = (\quad _0, \quad _1)$ for various taxa. In this example, $\kappa = (average\ stems\ per\ plot, average\ ln(dbh))$ is unknown and is estimated at the entity scale from a sample of plots (where dbh is the diameter at breast height).

Group	Taxon	95% Confidence Interval	β_0	β_1
Conifer	Abies, 0.35 spg[a]	±20%	–2.3123	2.3482

[a] spg is the specific gravity of wood on a green volume to dry-weight basis

The above table is not a complete replication of table 3-6 in chapter 3, only relevant information for the example in this chapter.

To determine the MVN PDF for θ , use the 95-percent confidence intervals in table 3-6, expressed as plus or minus some percentage. For a parameter β with estimated value b and 95-percent confidence interval $\pm d100\%$, where:

- Variance = $\left(\frac{bd}{1.96}\right)^2$
- Standard deviation = $\frac{|b|d}{1.96}$

Therefore, the corresponding PDF for β_0 is normal with mean -2.3123 and standard deviation $\frac{|-2.3123|(0.2)}{1.96} = 0.235949$.

Similarly, the corresponding PDF for β_1 is normal with mean 2.3482 and standard deviation $\frac{|2.3482|(0.2)}{1.96} = 0.239612$.

Table 3-6 does not provide covariances between estimated parameters. One conservative approach then is to maximize the variance of the emission factor by assuming the correlation between the estimates is either perfectly negative (if β_0 and β_1 have opposite signs) or perfectly positive (if β_0 and β_1 have the same signs). This assumption implies that the covariance is as shown in the equation below, where $\Sigma_{\theta,11}$ and $\Sigma_{\theta,22}$ are the variances:

$$\Sigma_{\theta,12} = \Sigma_{\theta,21} = sign(\beta_0\beta_1)\left(\Sigma_{\theta,11}\right)^{1/2}\left(\Sigma_{\theta,22}\right)^{1/2}$$

These computations imply that the PDF for θ is:

$$\begin{bmatrix}\beta_0\\ \beta_1\end{bmatrix} \sim MVN\left(\begin{bmatrix}-2.3123\\ 2.3482\end{bmatrix}, \begin{bmatrix}(0.235949)^2 & (-1)(0.235949)(0.2396122)\\ (-1)(0.235949)(0.2396122) & (0.2396122)^2\end{bmatrix}\right).$$

To determine the MVN PDF for κ in this example of woody tree biomass stock, sampling design, plus all measurements obtained from the sample, are required. Then this information helps estimates of the mean vector μ_κ and variance-covariance matrix Σ_κ.

In this example, one sample would be used to obtain estimates of various characteristics, e.g., average stems per plot for different taxa and average $ln(dbh)$ for different taxa. These estimates will be dependent, and proper estimation of Σ_κ will account for this dependence.

8.3.3 Implicit Model-Based Methods

Implicit model-based methods do not rely on any entity-scale measurements to determine emission factors. Their uncertainty is fully described with PDFs given elsewhere in this report. But those PDFs are not specified directly on model parameters, typically due to the complexity of these models, which represent biogeochemical processes. Instead, uncertainty is quantified based on comparisons of model-based predictions to field measurements from experimental studies (not from the entity under consideration). Examples include soil carbon stock changes and direct soil N_2O emissions, which are predicted with the DayCent ecosystem model and compared to experimental results from long-term field experiments to quantify uncertainty in model structure and parameterization.

The comparison of model predictions to field measurements uses a statistical model to account for independent variables (covariates) to explain some of the uncertainty in GHG emission predictions and to account for the correlations among measurements from the field experiments. The standard statistical model for this empirical method is a linear mixed effect (LME) model, with fixed effects to account for covariates and with random effects to account for spatial and temporal correlations. The implication of this statistical model at an entity scale is that the GHG emissions are modeled as:

$$G = \mu(A, F) + x^{\top}\beta + b$$

where:

$\mu(A, F)$	=	the output of the model with known activity data inputs A and with emission factors F that are implicitly defined
$x^{\top}$	=	a vector of known covariates at the entity scale (such as soil texture, management practice, climate variables, and related information about the management system and environmental conditions)
β	=	a vector of unknown fixed effect regression coefficients that have been estimated from the long-term field experiments
b	=	sum of one or more random effects that represent field-to-field variation that is not explained either by the model or by the fixed effects

Based on the estimation from the field experiments, the uncertainty in the fixed effects is described with a MVN PDF, with mean vector $\hat{\beta}$ and covariance matrix $\hat{\Sigma}$ from the fit of the LME. The uncertainty in the random effects is described with a normal PDF with mean 0 and with variance $\hat{\tau}^2$ equal to the sum of the estimated variances of all the random effects that are summed to create b.

For an entity with known activity data inputs A and known covariates $x^{\top}$, Monte Carlo UQ then proceeds with the following steps:

1. Start by setting the random number seed in the statistical software, so that results are reproducible.
2. For the rth replicate, draw a MVN random vector $\beta^{(r)} \sim MVN(\hat{\beta}, \hat{\Sigma})$, and select a normal random variable(s) $b^{(r)} \sim MVN(0, \hat{\tau}^2)$.
3. Compute $G^{(r)} = \mu(A, F) + x^{\top}\beta^{(r)} + b^{(r)}$.
4. Repeat, independently, for $r = 1,2, \ldots, M$. The resulting M Monte Carlo replicates $\{G_r\}_{r=1}^{M}$ represent a large, random sample from the unknown PDF $p_G(g)$.
5. Summarize the Monte Carlo results based on the median and 95-percent prediction interval, as described in section 8.2.4.

8.4 Extension of Monte Carlo for Unknown Activity Data Inputs

This chapter assumes activity data inputs are known at the entity scale. If these inputs are subject to some uncertainty, that uncertainty should be quantified with an appropriate PDF, $p_A(a)$. Assuming the uncertainty in the activity data is independent of the uncertainty in the emission factors, the Monte Carlo approach extends in a straightforward way. Proceeding as in section 8.2.3, generate a large number, M, of replicates of the possible GHG emissions with the following steps:

1. Start by setting the random number seed in the statistical software, so that results are reproducible.
2. For the rth replicate, draw a random activity data input A_r from the PDF $p_A(a)$and draw a random emission factor F_r from the PDF $p_F(f)$.
3. Use these random values as inputs to the method, yielding the rth random value $G_r = A_r F_r$ of the entity-level emission.
4. Repeat, independently, for $r = 1,2, \ldots, M$. The resulting M Monte Carlo replicates $\{G_r\}_{r=1}^{M}$ represent a large, random sample from the unknown PDF $p_G(g)$.

5. Summarize the Monte Carlo results based on the median and 95-percent prediction interval, as described in section 8.2.4.