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.

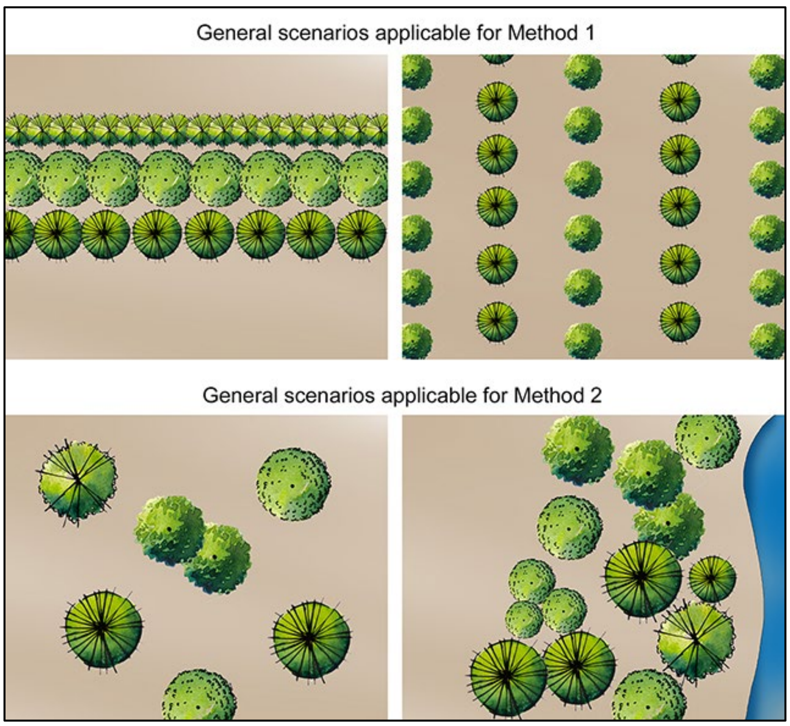


Figure 3-1. Plan Views Showing Which Method to Apply Based on Plant Arrangement

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:

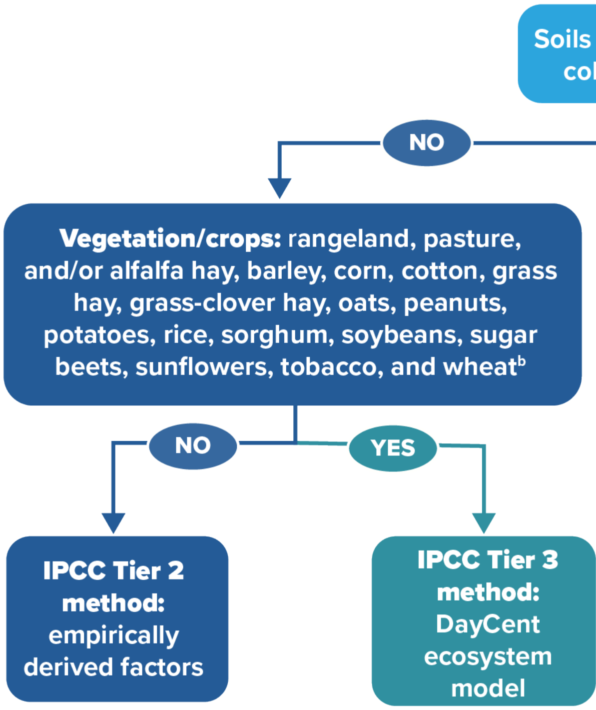
$\Delta TC_{mineral}$	=	annual change in mineral soil organic carbon stock plus biochar amendments (metric tons CO_2-eq)
$\Delta C_{mineral}$	=	annual change in mineral soil organic carbon stock (metric tons C)
ΔSOC_{BC}	=	annual change in soil organic carbon stock from biochar amendments (metric tons 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

[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:

- <u>Land-use change factors</u>. 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).

<u>Croplands</u>

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

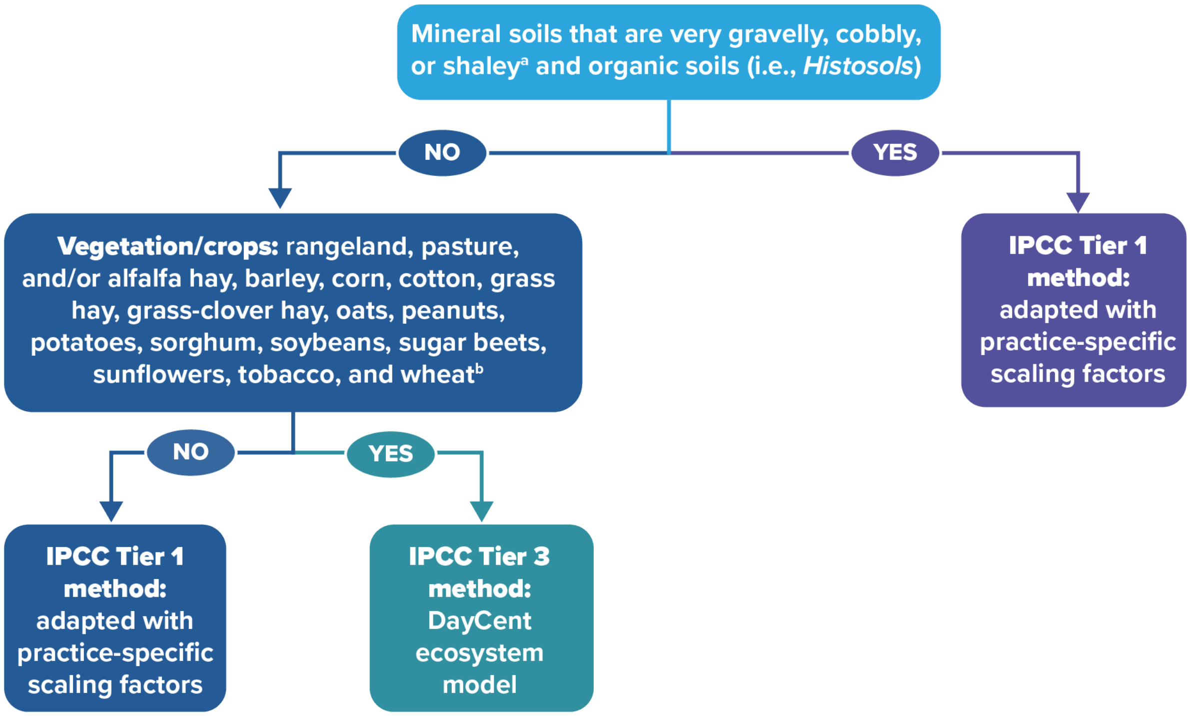
- Use the IPCC Tier 1 method for indirect soil N_2O emissions (Hergoualc'h et al., 2019).
- Use IPCC defaults for estimating the proportion of nitrogen that is subject to leaching, runoff, and volatilization. Inland parcels where the precipitation plus irrigation water input is less than 80 percent of 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	

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

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).

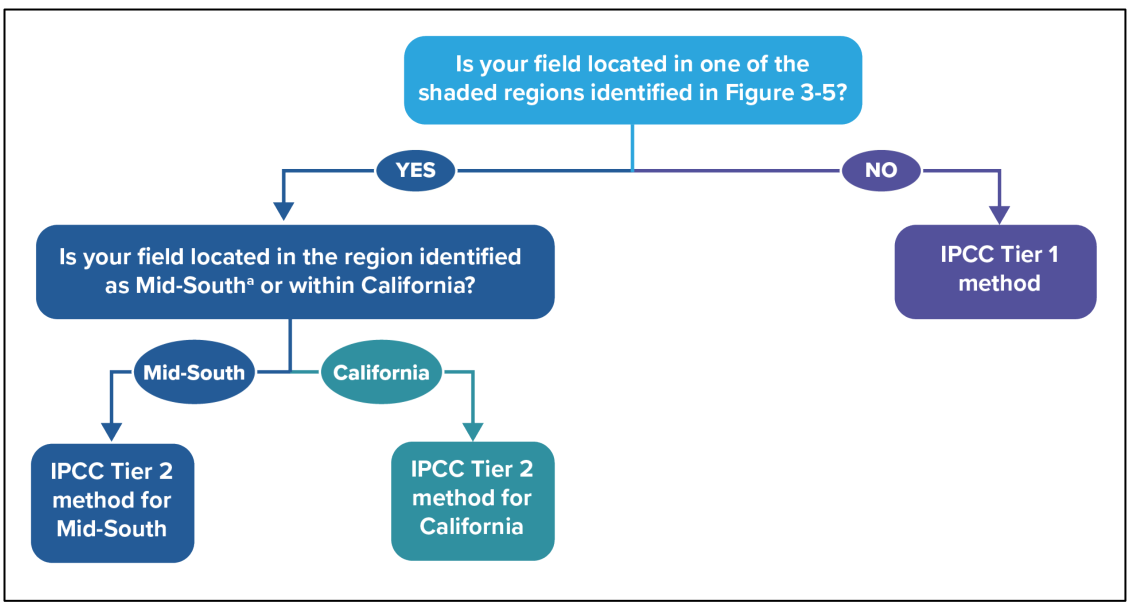
Equation 3-25: Annual Flooded Rice CH_4 Emissions

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

Where:

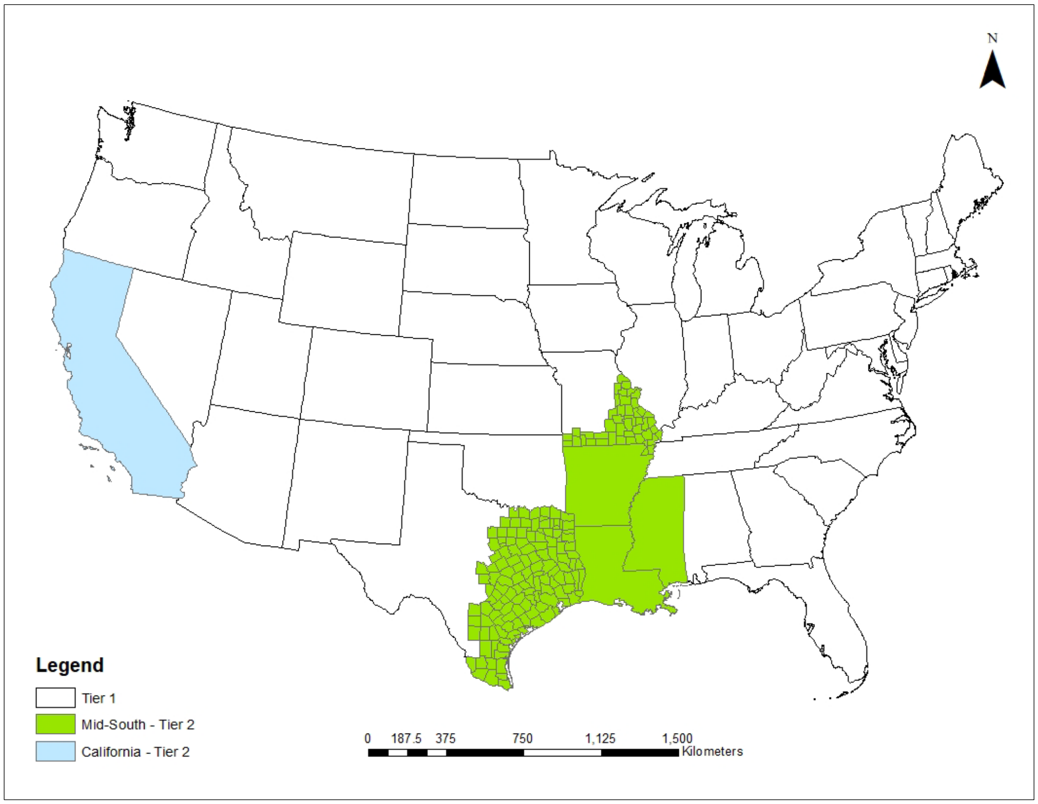
CH_{4Rice}	=	annual CH_4 emissions from rice cultivation (metric tons CO_2-eq)
CH_{4GWP}	=	global warming potential for CH_4 (metric tons CO_2-eq/metric tons CH_4)
EF_i	=	integrated daily emission factor based on management for each growing season (kg CH_4/ha/day)
t	=	cultivation period of rice for each 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.

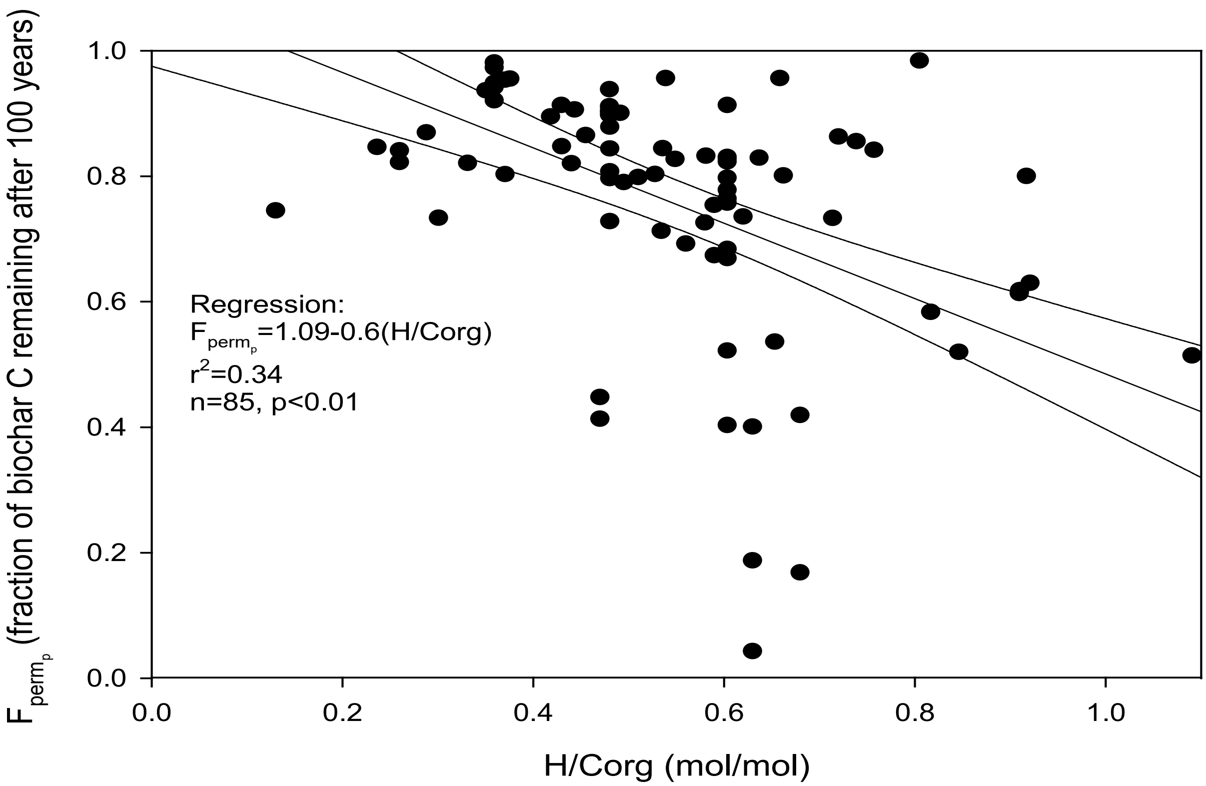
The model simulates management practices influencing SOC pools. These practices include addition of carbon in manure and other organic amendments, such as compost, wood chips, and biochar; tillage intensity; residue management (retention of residues in field without incorporation, retention in the field 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.

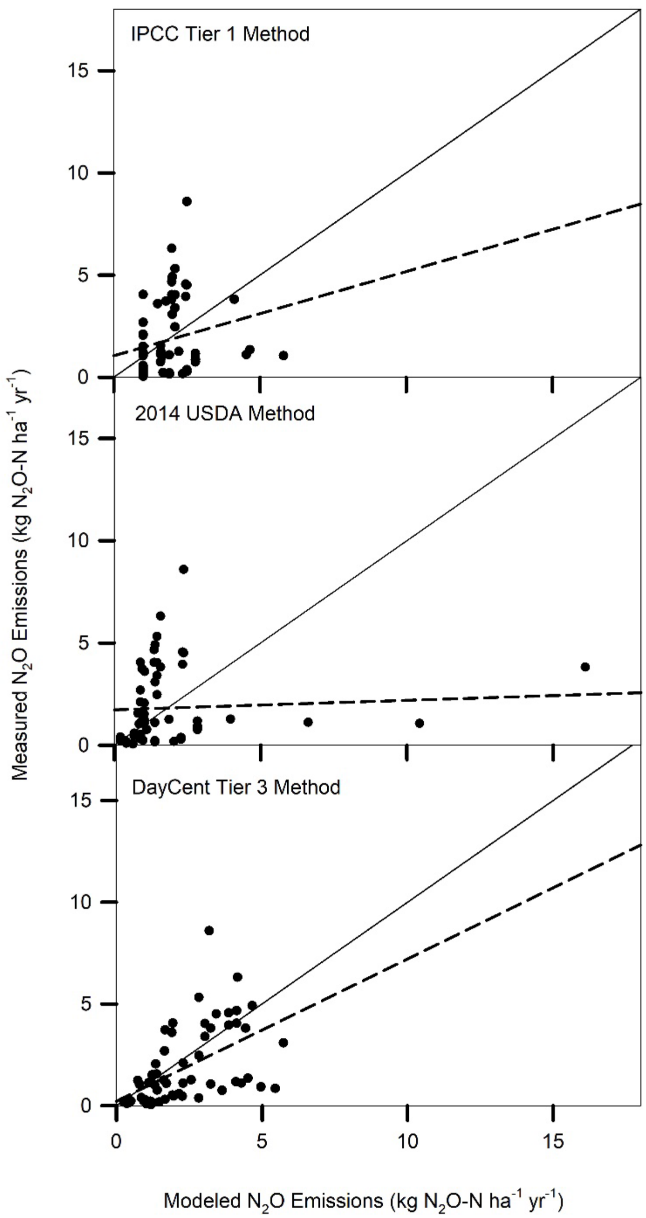
The fitted regression line for the DayCent model is closer to the reference line and has the lowest r^2 value for the fit to the observed emissions, followed by the IPCC method and the 2014 USDA entity-scale reporting method. Moreover, the fitted regression line for the 2014 USDA entity-scale reporting 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).

The studies used in the meta-analysis for the base CH_4 flux for natural vegetation and management factors are provided below:

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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.