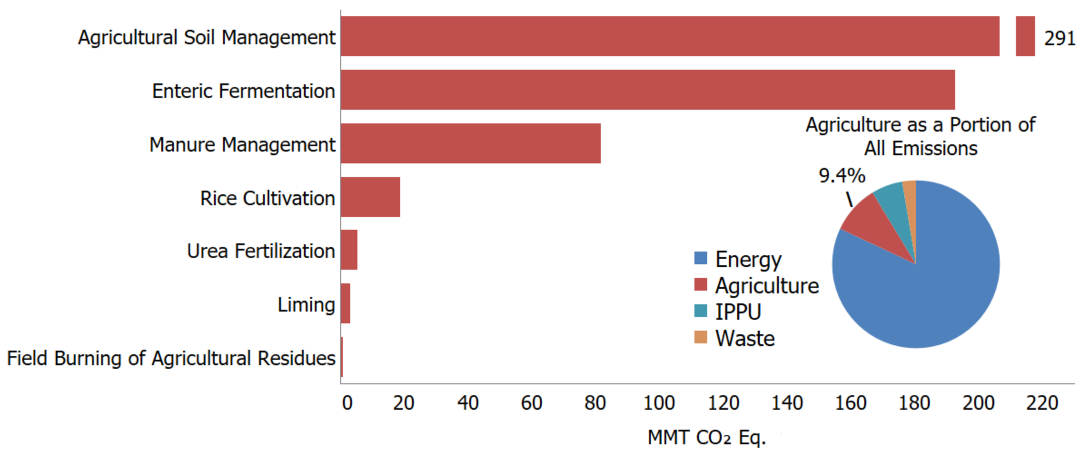
5. Agriculture

Agricultural activities contribute directly to emissions of greenhouse gases through a variety of processes. This chapter provides an assessment of methane (CH_4) from enteric fermentation, livestock manure management, rice cultivation and field burning of agricultural residues; nitrous oxide (N_2O) emissions from agricultural soil management, livestock manure management, and field burning of agricultural residues; as well as carbon dioxide (CO_2) emissions from liming and urea fertilization (see Figure 5-1). Additional CO_2, CH_4 and N_2O fluxes from agriculture-related land-use and land-use conversion activities, such as cultivation of cropland, management on grasslands, grassland fires, aquaculture, and conversion of forest land to cropland, are presented in the Land Use, Land-Use Change, and Forestry (LULUCF) chapter. Carbon dioxide emissions from stationary and mobile on-farm energy use and CH_4 and N_2O emissions from stationary on-farm energy use are reported in the Energy chapter under the Industrial sector emissions. Methane and N_2O emissions from mobile on-farm energy use are reported in the Energy chapter under mobile fossil fuel combustion emissions.

Figure 5-1: 2022 Agriculture Sector Greenhouse Gas Emission Sources



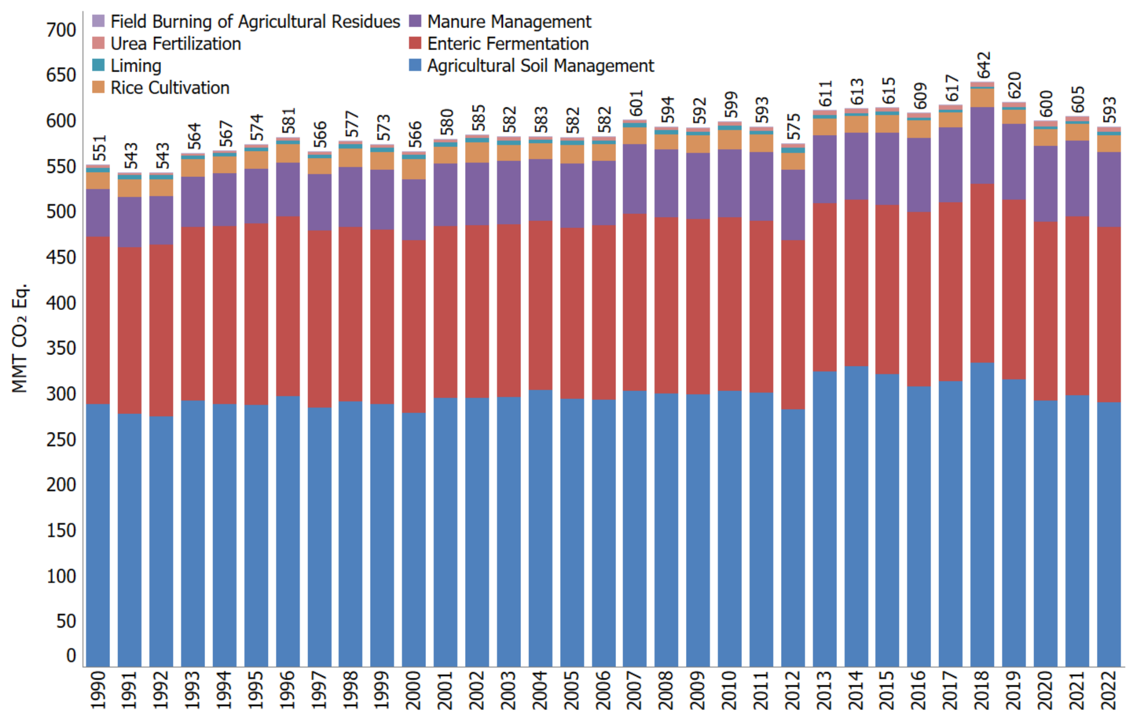
In 2022, the Agriculture sector was responsible for emissions of 593.4 MMT CO_2 Eq.,[1] or 9.4 percent of total U.S. greenhouse gas emissions. Emissions of N_2O by agricultural soil management through activities such as fertilizer

[1] Following the current reporting requirements under the Paris Agreement and the United Nations Framework Convention on Climate Change (UNFCCC), this Inventory report presents CO_2 equivalent values based on the IPCC *Fifth Assessment Report* (AR5) GWP values. See the Introduction chapter as well as Chapter 9 for more information.

application and other agricultural practices that increased nitrogen availability in the soil was the largest source of U.S. N_2O emissions, accounting for 74.6 percent, and the largest source of emissions from the Agriculture sector, accounting for 49.0 percent of total sector emissions. Methane emissions from enteric fermentation and manure management represented 27.4 percent and 9.2 percent of total CH_4 emissions from anthropogenic activities, respectively, and 32.5 and 10.9 percent of Agriculture sector emissions, respectively. Of all domestic animal types, beef and dairy cattle were the largest emitters of CH_4. Rice cultivation and field burning of agricultural residues were minor sources of CH_4. Manure management and field burning of agricultural residues were also small sources of N_2O emissions. Urea fertilization and liming each accounted for 0.1 percent of total CO_2 emissions from anthropogenic activities.

Table 5-1 and Table 5-2 present emission estimates for the Agriculture sector. Between 1990 and 2022, CO_2 and CH_4 emissions from agricultural activities increased by 21 percent and 14.5 percent, respectively, while N_2O emissions from agricultural activities fluctuated from year to year but increased by 1.9 percent overall. Trends in sources of agricultural emissions over the 1990 to 2022 time series are shown in Figure 5-2.

Figure 5-2: Trends in Agriculture Sector Greenhouse Gas Emission Sources



Each year, some emission estimates in the Agriculture sector of the *Inventory* are recalculated and revised with improved methods and/or data. In general, recalculations are made to the U.S. greenhouse gas emission estimates either to incorporate new methodologies or, most commonly, to update recent historical data. These improvements are implemented consistently across the previous *Inventory's* time series (i.e., 1990 through 2021) to ensure that the trend is accurate. This year's key improvements include: manure management: updates to beef feedlot and poultry waste management system (WMS) data; field burning of agricultural residues: addition of residue burning from sugarcane. For more information on specific methodological updates, please see the Recalculations Discussions within the respective source category sections of this chapter. In total, the methodological and historic data improvements made to the Agriculture sector in this *Inventory* increased greenhouse gas emission estimates by an average of 5.3 MMT CO_2 Eq. (0.9 percent) across the time series.

Emissions reported in the Agriculture chapter include those from all states; however, for Hawaii and Alaska some agricultural practices that can increase nitrogen availability in the soil, and thus cause N_2O emissions, are not included (see chapter sections on Uncertainty and Time-Series Consistency and Planned Improvements for more details). Emissions from the Agriculture sector occurring in U.S. Territories and the District of Columbia are not estimated due to incomplete data, with the exception of urea fertilization in Puerto Rico. EPA continues to identify and review available data on an ongoing basis to include agriculture emissions from U.S. Territories, to the extent they are occurring, in future *Inventories*. Other minor outlying U.S. Territories in the Pacific Islands have no permanent populations (e.g., Baker Island) and therefore EPA assumes no agricultural activities are occurring. See Annex 5 for more information on EPA's assessment of the sources not included in this *Inventory*.

Table 5-1: Emissions from Agriculture (MMT CO_2 Eq.)

Gas/Source	1990	2005	2018	2019	2020	2021	2022
CO_2	**7.1**	**7.9**	**7.2**	**7.2**	**8.0**	**7.6**	**8.6**
Urea Fertilization	2.4	3.5	4.9	5.0	5.1	5.2	5.3
Liming	4.7	4.4	2.2	2.2	2.9	2.4	3.3
CH_4	**241.7**	**264.4**	**285.0**	**280.2**	**282.4**	**281.8**	**276.8**
Enteric Fermentation	183.1	188.2	196.8	197.3	196.3	196.5	192.6
Manure Management	39.1	55.0	67.7	66.7	66.9	66.4	64.7
Rice Cultivation	18.9	20.6	19.9	15.6	18.6	18.3	18.9
Field Burning of Agricultural Residues	0.5	0.6	0.6	0.7	0.6	0.6	0.6
N_2O	**302.3**	**309.5**	**350.2**	**332.6**	**309.2**	**315.3**	**308.0**
Agricultural Soil Management	288.8	294.1	333.4	315.6	292.1	298.0	290.8
Manure Management	13.4	15.2	16.6	16.8	16.9	17.1	17.0
Field Burning of Agricultural Residues	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Total	**551.1**	**581.8**	**642.4**	**620.1**	**599.7**	**604.8**	**593.4**

Note: Totals may not sum due to independent rounding.

Table 5-2: Emissions from Agriculture (kt)

Gas/Source	1990	2005	2018	2019	2020	2021	2022
CO_2	**7,106**	**7,856**	**7,176**	**7,237**	**8,019**	**7,616**	**8,595**
Urea Fertilization	2,417	3,504	4,936	5,034	5,132	5,229	5,327
Liming	4,690	4,351	2,240	2,203	2,887	2,387	3,268
CH_4	**8,633**	**9,444**	**10,179**	**10,008**	**10,087**	**10,066**	**9,885**
Enteric Fermentation	6,539	6,722	7,028	7,045	7,010	7,017	6,878
Manure Management	1,398	1,964	2,418	2,382	2,390	2,373	2,312
Rice Cultivation	677	735	711	558	664	653	674
Field Burning of Agricultural Residues	19	23	22	23	22	22	22
N_2O	**1,141**	**1,168**	**1,322**	**1,255**	**1,167**	**1,190**	**1,162**
Agricultural Soil Management	1,090	1,110	1,258	1,191	1,102	1,124	1,097
Manure Management	50	57	63	63	64	65	64
Field Burning of Agricultural Residues	1	1	1	1	1	1	1

Note: Totals by gas may not sum due to independent rounding.

Box 5-1: Methodological Approach for Estimating and Reporting U.S. Emissions and Removals

Consistent with Article 13.7(a) of the Paris Agreement and Article 4.1(a) of the UNFCCC as well as relevant decisions under those agreements, the emissions and removals presented in this report and this chapter are organized by source and sink categories and calculated using internationally-accepted methods provided by the Intergovernmental Panel on Climate Change (IPCC) in the *2006 IPCC Guidelines for National Greenhouse Gas Inventories* (*2006 IPCC Guidelines*). Additionally, the calculated emissions and removals in a given year for the United States are presented in a common format in line with the reporting guidelines for the reporting of inventories under the Paris Agreement and the UNFCCC. The Parties' use of consistent methods to calculate emissions and removals for their inventories helps to ensure that these reports are comparable. The presentation of emissions provided in the Agriculture chapter does not preclude alternative examinations (e.g., economic sectors). Rather, this chapter presents emissions in a common format consistent with how Parties are to report their national inventories under the Paris Agreement and the UNFCCC. The report itself, and this chapter, follow this common format and provide an explanation of the application of methods used to calculate emissions from agricultural activities.

5.1 Enteric Fermentation (CRT Source Category 3A)

Methane is produced as part of normal digestive processes in animals. During digestion, microbes resident in an animal's digestive system ferment food consumed by the animal. This microbial fermentation process, referred to as enteric fermentation, produces CH_4 as a byproduct, which can be exhaled or eructated by the animal. The amount of CH_4 produced and emitted by an individual animal depends primarily upon the animal's digestive system, and the amount and type of feed it consumes.[2]

Ruminant animals (e.g., cattle, buffalo, sheep, goats, and camels) are the major emitters of CH_4 because of their unique digestive system. Ruminants possess a rumen, or large "fore-stomach," in which microbial fermentation breaks down the feed they consume into products that can be absorbed and metabolized. The microbial fermentation that occurs in the rumen enables them to digest coarse plant material that non-ruminant animals cannot. Ruminant animals, consequently, have the highest CH_4 emissions per unit of body mass among all animal types.

Non-ruminant animals (e.g., swine, horses, and mules and asses) also produce CH_4 emissions through enteric fermentation, although this microbial fermentation occurs in the large intestine. These non-ruminants emit significantly less CH_4 on a per-animal-mass basis than ruminants because the capacity of the large intestine to produce CH_4 is lower.

In addition to the type of digestive system, an animal's feed quality and feed intake also affect CH_4 emissions. In general, lower feed quality and/or higher feed intake leads to higher CH_4 emissions. Feed intake is positively correlated to animal size, growth rate, level of activity and production (e.g., milk production, wool growth, pregnancy, or work). Therefore, feed intake varies among animal types as well as among different management practices for individual animal types (e.g., animals in feedlots or grazing on pasture).

Methane emission estimates from enteric fermentation are provided in Table 5-3 and Table 5-4. Total livestock CH_4 emissions in 2022 were 192.6 MMT CO_2 Eq. (6,878 kt). Beef cattle remain the largest contributor of CH_4 emissions from enteric fermentation, accounting for 71 percent in 2022. Emissions from dairy cattle in 2022 accounted for 25 percent, and the remaining methane emissions were from swine, horses, sheep, goats, American bison, mules and asses.[3]

[2] CO_2 emissions from livestock are not estimated because annual net CO_2 emissions are assumed to be zero – the CO_2 photosynthesized by plants is returned to the atmosphere as respired CO_2 (IPCC 2006).

[3] Enteric fermentation emissions from poultry are not estimated because no IPCC method has been developed for determining enteric fermentation CH_4 emissions from poultry; at this time, developing a country-specific method would require a disproportionate amount of resources given the small magnitude of this source category. Enteric fermentation emissions from camels are not estimated because there is no significant population of camels in the United States. Given the insignificance of estimated camel emissions in terms of the overall level and trend in national emissions, there are no immediate improvement

Table 5-3: CH_4 Emissions from Enteric Fermentation (MMT CO_2 Eq.)

Livestock Type	1990	2005	2018	2019	2020	2021	2022
Beef Cattle	132.8	139.6	141.2	141.7	140.5	140.3	137.0
Dairy Cattle	43.3	41.3	48.6	48.5	48.8	49.4	48.9
Swine	2.3	2.6	3.1	3.2	3.2	3.1	3.1
Horses	1.1	2.0	1.4	1.3	1.2	1.1	1.0
Sheep	2.9	1.5	1.3	1.3	1.3	1.3	1.3
Goats	0.6	0.7	0.7	0.7	0.7	0.7	0.7
American Bison	0.1	0.5	0.4	0.4	0.5	0.5	0.5
Mules and Asses	+	0.1	0.1	0.1	0.1	0.1	0.1
Total	**183.1**	**188.2**	**196.8**	**197.3**	**196.3**	**196.5**	**192.6**

+ Does not exceed 0.05 MMT CO_2 Eq.
Note: Totals may not sum due to independent rounding.

Table 5-4: CH_4 Emissions from Enteric Fermentation (kt CH_4)

Livestock Type	1990	2005	2018	2019	2020	2021	2022
Beef Cattle	4,742	4,986	5,042	5,062	5,018	5,010	4,891
Dairy Cattle	1,547	1,473	1,737	1,732	1,743	1,764	1,748
Swine	81	92	110	115	115	111	110
Horses	40	70	48	46	43	40	37
Sheep	102	55	47	47	47	47	46
Goats	23	26	24	25	25	25	25
American Bison	4	17	15	16	16	17	17
Mules and Asses	1	2	3	3	3	3	3
Total	**6,539**	**6,722**	**7,028**	**7,045**	**7,010**	**7,017**	**6,878**

Note: Totals may not sum due to independent rounding.

From 1990 to 2022, emissions from enteric fermentation have increased by 5.2 percent. From 2021 to 2022, emissions decreased by 2 percent, largely driven by a decrease in beef cattle populations. While emissions generally follow trends in cattle populations, there are exceptions across the time series. For example, while dairy cattle emissions increased 13 percent over the entire time series, the population has declined by 4.5 percent, and milk production increased 45.9 percent (USDA 2021; USDA 2022). These trends indicate that while emissions per head are increasing, emissions per unit of product (i.e., meat, milk) are decreasing.

Generally, from 1990 to 1995 emissions from beef cattle increased and then decreased from 1996 to 2004. These trends were mainly due to fluctuations in beef cattle populations and increased digestibility of feed for feedlot cattle. Beef cattle emissions generally increased from 2004 to 2007, as beef cattle populations increased, and an extensive literature review indicated a trend toward a decrease in feed digestibility for those years. Beef cattle emissions decreased again from 2007 to 2014, as populations again decreased, but increased from 2015 to 2018, consistent with another increase in population over those same years. Emissions and populations generally declined from 2018 to 2022, with a slight post-pandemic rebound in 2021.

Emissions from dairy cattle generally trended downward from 1990 to 2004, along with an overall dairy cattle population decline during the same period. Similar to beef cattle, dairy cattle emissions rose from 2004 to 2007 due to population increases and a decrease in feed digestibility (based on an analysis of more than 350 dairy cow diets used by producers across the United States). Dairy cattle emissions continued to trend upward from 2007 to 2018, generally in line with dairy cattle population changes.

plans to include this emissions category in the *Inventory*. See Annex 5 for more information on significance of estimated camel emissions.

Regarding trends in other animals, populations of sheep have steadily declined, with an overall decrease of 55 percent since 1990. Horse populations peaked in 2007 and have been declining by an average of 4 percent annually since 2007, with their current population 6 percent lower than it was in 1990. Goat populations increased by about 20 percent through 2007 followed by a steady decrease through 2012. Since 2012, goat populations continue to increase by 1 percent annually. Swine populations have trended upward through most of the time series, increasing 43 percent from 1990 to 2020. However, swine populations decreased by around 5 percent from 2020 to 2022. The population of American bison more than quadrupled over the 1990 to 2022 time period, while the population of mules and asses increased by a factor of five.

Methodology and Time-Series Consistency

Livestock enteric fermentation emission estimate methodologies fall into two categories: cattle and other domesticated animals. Cattle, due to their large population, large size, and particular digestive characteristics, account for the majority of enteric fermentation CH_4 emissions from livestock in the United States. A more detailed methodology (i.e., IPCC Tier 2) was therefore applied to estimate emissions for all cattle. Emission estimates for other domesticated animals (horses, sheep, swine, goats, American bison, and mules and asses) were estimated using the IPCC Tier 1 approach, as suggested by the *2006 IPCC Guidelines* (see the Planned Improvements section).

While the large diversity of animal management practices cannot be precisely characterized and evaluated, significant scientific literature exists that provides the necessary data to estimate cattle emissions using the IPCC Tier 2 approach. The Cattle Enteric Fermentation Model (CEFM), developed by EPA and used to estimate cattle CH_4 emissions from enteric fermentation using IPCC's Tier 2 method, incorporates this information and other analyses of livestock population, feeding practices, and production characteristics.

Methodological approaches, changes to historic data, and other parameters were applied to the entire time series to ensure consistency in emissions estimates from 1990 through 2022. See Annex 3.10 for more detailed information on the methodology and data used to calculate CH_4 emissions from enteric fermentation. In addition, variables and the resulting emissions are also available at the state level in Annex 3.10.

Inventory Methodology for Cattle

National cattle population statistics were disaggregated into the following cattle sub-populations:

- Dairy Cattle
  - Calves
  - Heifer Replacements
  - Cows
- Beef Cattle
  - Calves
  - Heifer Replacements
  - Heifer and Steer Stockers
  - Animals in Feedlots (Heifers and Steer)
  - Cows
  - Bulls

Calf birth rates, end-of-year population statistics, detailed feedlot placement information, and slaughter weight data were used to create a transition matrix that models cohorts of individual animal types and their specific emission profiles. The key variables tracked for each of the cattle population categories are described in Annex 3.10. These variables include performance factors such as pregnancy and lactation as well as average weights and weight gain. Annual cattle population data were obtained from the U.S. Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS) *QuickStats* database (USDA 2023).

Diet characteristics were estimated by region for dairy, grazing beef, and feedlot beef cattle. These diet characteristics were used to calculate digestible energy (DE) values (expressed as the percent of gross energy intake digested by the animal) and CH_4 conversion rates (Y_m) (expressed as the fraction of gross energy converted to CH_4) for each regional population category. The IPCC recommends Y_m ranges of 3.0±1.0 percent for feedlot cattle and 6.5±1.0 percent for other well-fed cattle consuming temperate-climate feed types (IPCC 2006). Given the availability of detailed diet information for different regions and animal types in the United States, DE and Y_m values unique to the United States were developed. The diet characterizations and estimation of DE and Y_m values were based on information from state agricultural extension specialists, a review of published forage quality studies and scientific literature, expert opinion, and modeling of animal physiology.

The diet characteristics for dairy cattle were based on Donovan (1999) and an extensive review of nearly 20 years of literature from 1990 through 2009. Estimates of DE were national averages based on the feed components of the diets observed in the literature for the following year groupings: 1990 through 1993, 1994 through 1998, 1999 through 2003, 2004 through 2006, 2007, and 2008 onward.[4] Base year Y_m values by region were estimated using Donovan (1999). As described in ERG (2016), a ruminant digestion model (COWPOLL, as selected in Kebreab et al. 2008) was used to evaluate Y_m for each diet evaluated from the literature, and a function was developed to adjust regional values over time based on the national trend. Dairy replacement heifer diet assumptions were based on the observed relationship in the literature between dairy cow and dairy heifer diet characteristics.

For feedlot animals, the DE and Y_m values used for 1990 were recommended by Johnson (1999). Values for DE and Y_m for 1991 through 1999 were linearly extrapolated based on the 1990 and 2000 data. DE and Y_m values for 2000 onwards were based on survey data in Galyean and Gleghorn (2001) and Vasconcelos and Galyean (2007).

For grazing beef cattle, Y_m values were based on Johnson (2002), DE values for 1990 through 2006 were based on specific diet components estimated from Donovan (1999), and DE values from 2007 onwards were developed from an analysis by Archibeque (2011), based on diet information in Preston (2010) and USDA-APHIS:VS (2010). Weight and weight gains for cattle were estimated from Holstein (2010), Doren et al. (1989), Enns (2008), Lippke et al. (2000), Pinchack et al. (2004), Platter et al. (2003), Skogerboe et al. (2000), and expert opinion. See Annex 3.10 for more details on the method used to characterize cattle diets and weights in the United States.

Calves younger than 4 months are not included in emission estimates because calves consume mainly milk and the IPCC recommends the use of a Y_m of zero for all juveniles consuming only milk. Diets for calves aged 4 to 6 months are assumed to go through a gradual weaning from milk decreasing to 75 percent at 4 months, 50 percent at age 5 months, and 25 percent at age 6 months. The portion of the diet made up with milk still results in zero emissions. For the remainder of the diet, beef calf DE and Y_m are set equivalent to those of beef replacement heifers, while dairy calf DE is set equal to that of dairy replacement heifers and dairy calf Y_m is provided at 4 and 7 months of age by Soliva (2006). Estimates of Y_m for 5- and 6-month-old dairy calves are linearly interpolated from the values provided for 4 and 7 months.

To estimate CH_4 emissions, the population was divided into state, age, sub-type (i.e., dairy cows and replacements, beef cows and replacements, heifer and steer stockers, heifers and steers in feedlots, bulls, beef calves 4 to 6 months, and dairy calves 4 to 6 months), and production (i.e., pregnant, lactating) groupings to more fully capture differences in CH_4 emissions from these animal types. The transition matrix was used to simulate the age and weight structure of each sub-type on a monthly basis in order to more accurately reflect the fluctuations that occur throughout the year. Cattle diet characteristics were then used in conjunction with Tier 2 equations from IPCC (2006) to produce CH_4 emission factors for the following cattle types: dairy cows, beef cows, dairy replacements, beef replacements, steer stockers, heifer stockers, steer feedlot animals, heifer feedlot animals, bulls, and calves. To estimate emissions from cattle, monthly population data from the transition matrix were multiplied by the calculated emission factor for each cattle type in each state. More details are provided in Annex 3.10.

[4] Due to inconsistencies in the 2003 literature values, the 2002 values were used for 2003 as well.

Non-Cattle Livestock

Emission estimates for other animal types were based on average emission factors (Tier 1 default IPCC emission factors) representative of entire populations of each animal type. The methodology is in accordance with the methodological decision tree for methane emissions from enteric fermentation (IPCC 2019). Methane emissions from these animals accounted for a minor portion of total CH_4 emissions from livestock in the United States from 1990 through 2022. Additionally, the variability in emission factors for each of these other animal types (e.g., variability by age, production system, and feeding practice within each animal type) is less than that for cattle.

Annual livestock population data for 1990 to 2022 for sheep, swine, goats, horses, mules and asses, and American bison were obtained for available years from USDA-NASS (USDA 2023; USDA 2019). Horse, goat, and mule and ass population data were available for 1987, 1992, 1997, 2002, 2007, 2012, and 2017 (USDA 2019); the remaining years between 1990 and 2022 were interpolated and extrapolated from the available estimates (with the exception of goat populations being held constant between 1990 and 1992). American bison population estimates were available from USDA for 2002, 2007, 2012, and 2017 (USDA 2019) and from the National Bison Association (1999) for 1990 through 1999. Additional years were based on observed trends from the National Bison Association (1999), interpolation between known data points, and extrapolation beyond 2012, as described in more detail in Annex 3.10.

Methane emissions from sheep, goats, swine, horses, American bison, and mules and asses were estimated by using emission factors utilized in Crutzen et al. (1986, cited in IPCC 2006; IPCC 2019). These emission factors are representative of typical animal sizes, feed intakes, and feed characteristics in developed countries. For American bison, the emission factor for buffalo was used and adjusted based on the ratio of live weights to the 0.75 power. The methodology is the same as that recommended by IPCC (2006).

Uncertainty

A quantitative uncertainty analysis for this source category was performed using the IPCC-recommended Approach 2 uncertainty estimation methodology based on a Monte Carlo stochastic simulation technique as described in ICF (2003). These uncertainty estimates were developed for the 1990 through 2001 *Inventory* (i.e., 2003 submission to the UNFCCC). While there are plans to update the uncertainty to reflect recent methodological updates and forthcoming changes (see Planned Improvements, below), at this time the uncertainty estimates were directly applied to the 2022 emission estimates in this *Inventory*.

A total of 185 primary input variables (177 for cattle and 8 for non-cattle) were identified as key input variables for the uncertainty analysis. A normal distribution was assumed for almost all activity- and emission factor-related input variables. Triangular distributions were assigned to three input variables (specifically, cow-birth ratios for the three most recent years included in the 2001 model run) to ensure only positive values would be simulated. For some key input variables, the uncertainty ranges around their estimates (used for *Inventory* estimation) were collected from published documents and other public sources; others were based on expert opinion and best estimates. In addition, both endogenous and exogenous correlations between selected primary input variables were modeled. The exogenous correlation coefficients between the probability distributions of selected activity-related variables were developed through expert judgment.

Among the individual cattle sub-source categories, beef cattle account for the largest amount of CH_4 emissions, as well as the largest degree of uncertainty in the emission estimates—due mainly to the difficulty in estimating the diet characteristics for grazing members of this animal group. Among non-cattle, horses represent the largest percent of uncertainty in the uncertainty analysis last conducted in 2001 because the Food and Agricultural Organization (FAO) of the United Nations population estimates used for horses at that time had a higher degree of uncertainty than for the USDA population estimates used for swine, goats, and sheep. The horse populations are drawn from the same USDA source as the other animal types[5], and therefore the uncertainty range around horses is likely overestimated. Cattle calves, American bison, mules and asses were excluded from the initial uncertainty estimate because they were not included in emission estimates at that time.

The uncertainty ranges associated with the activity data-related input variables were ±10 percent or lower. However, for many emission factor-related input variables, the lower- and/or the upper-bound uncertainty estimates were over 20 percent. The results of the quantitative uncertainty analysis are summarized in Table 5-5. Based on this analysis, enteric fermentation CH_4 emissions in 2022 were estimated to be between 171.4 and 227.2 MMT CO_2 Eq. at a 95 percent confidence level, which indicates a range of 11 percent below to 18 percent above the 2022 emission estimate of 192.6 MMT CO_2 Eq.

As a comparison to the Approach 2, a quantitative uncertainty analysis for this source category was performed using the IPCC (2006) recommended Approach 1 based on simple error propagation. Enteric fermentation CH_4 emissions in 2022 were estimated to be between 132.6 and 252.6 MMT CO_2 Eq., which indicates a range of ±31 percent above and below the 2022 emission estimate of 192.6 MMT CO_2 Eq. A ±10 percent uncertainty factor is applied to the activity data (e.g., animal populations), and a ±40 percent default uncertainty factor is applied to the emission factors (IPCC 2019).

Table 5-5: Approach 2 Quantitative Uncertainty Estimates for CH_4 Emissions from Enteric Fermentation (MMT CO_2 Eq. and Percent)

Source	Gas	2022 Emission Estimate (MMT CO_2 Eq.)	Uncertainty Range Relative to Emission Estimate[a, b, c] (MMT CO_2 Eq.)		(%)	
			Lower Bound	Upper Bound	Lower Bound	Upper Bound
Enteric Fermentation	CH_4	192.6	171.4	227.2	-11%	+18%

[a] Range of emissions estimates predicted by Monte Carlo stochastic simulation for a 95 percent confidence interval.
[b] Note that the relative uncertainty range was estimated with respect to the 2001 emission estimates from the 2003 submission and applied to the 2022 estimates.
[c] The overall uncertainty calculated in 2003, and applied to the 2022 emission estimate, did not include uncertainty estimates for calves, American bison, and mules and asses. Additionally, for bulls the emissions estimate was based on the Tier 1 methodology. Since bull emissions are now estimated using the Tier 2 method, the uncertainty surrounding their estimates is likely lower than indicated by the previous uncertainty analysis.

QA/QC and Verification

In order to ensure the quality of the emission estimates from enteric fermentation, the General (IPCC Tier 1) and category-specific (Tier 2) Quality Assurance/Quality Control (QA/QC) procedures were implemented consistent with the *U.S. Inventory QA/QC Plan* outlined in Annex 8. Category-specific or Tier 2 QA procedures included independent review of emission estimate methodologies from previous *Inventories*.

As part of the quality assurance process, average implied emissions factors for U.S. dairy and beef cattle were developed based on CEFM output and compared to emission factors for other countries provided by IPCC (2006). This comparison is discussed in further detail in Annex 3.10.

Over the past few years, particular importance has been placed on harmonizing the data exchange between the enteric fermentation and manure management source categories. The current *Inventory* utilizes the same transition matrix from the CEFM for estimating cattle populations and weights for both source categories, and the CEFM is used to output volatile solids and nitrogen excretion estimates using the diet assumptions in the model in

[5] The change from using FAO data to USDA data for horse populations took place during the development of the 1990 through 2011 *Inventory*, published in 2013.

conjunction with the energy balance equations from the IPCC (2006). This approach facilitates the QA/QC process for both of these source categories.

Recalculations Discussion

In the previous *Inventory*, 1990 to 2020 estimates were retained from the 1990 through 2020 *Inventory*, and 2021 estimates were based on a simplified approach that used emission factors and extrapolated population estimates for all animals. For the current *Inventory*, the CEFM was used for cattle for all years, resulting in different estimates for 2021 than the prior *Inventory*.

For cattle, there were also changes to emissions resulting from activity data changes, including:

- The USDA published minor data revisions that EPA incorporated into the CEFM:
  - Calf birth data were revised for 2020;
  - Dairy cow milk production values were updated for several states for 2020;
  - Slaughter data were revised for 2020.
- EPA revised annual milk fat values in the CEFM from 2000 through 2021 with updated annual values from USDA's Economic Research Services (ERS) dairy data (USDA 2022). In the previous *Inventory*, EPA derived annual averages from monthly ERS milk fat values, which is no longer available beyond 2010 (USDA 2021).
- EPA discovered and corrected an error within the CEFM related to the urinary energy input used for feedlot cattle, which affected VS results for this animal group. The urinary energy default was updated from 0.04 to 0.02 for feedlot cattle. These updates will affect values in Section 5.2 Manure Management.

Planned Improvements

Regular annual data reviews and updates are necessary to maintain an emissions inventory that reflects the current base of knowledge. In addition to the documented approaches currently used to address data availability, EPA conducts the following annual assessments to identify and determine the applicability of newer data when updating the estimates to extend time series each year:

- Further research to improve the estimation of dry matter intake (as gross energy intake) using data from appropriate production systems;
- Updating input variables that are from older data sources, such as beef births by month, beef and dairy annual calving rates, and beef cow lactation rates;
- Investigating the availability of data for dairy births by month, to replace the current assumption that births are evenly distributed throughout the year;
- Investigating the availability of annual data for the DE, Y_m, and crude protein values of specific diet and feed components for grazing and feedlot animals (including investigating the availability of existing models to estimate diet characteristics, as well as the use and impact of feed additives on emissions);
- Further investigation on additional sources or methodologies for estimating DE for dairy cattle, given the many challenges in characterizing dairy cattle diets;
- Further evaluation of the assumptions about weights and weight gains for beef cows, such that trends beyond 2007 are updated, rather than held constant; and
- Further evaluation of the estimated weight for dairy cows (i.e., 1,500 lbs) that is based solely on Holstein cows as mature dairy cow weight is likely slightly overestimated, based on knowledge of the breeds of dairy cows in the United States.

Depending upon the outcome of ongoing investigations, future improvement efforts for enteric fermentation could include some of the following options which are additional to the regular updates, and may or may not have implications for regular updates once addressed:

- Potentially updating to a Tier 2 methodology for other animal types (i.e., sheep, swine, goats, horses). Efforts to move to Tier 2 will consider the emissions significance of livestock types;
- Investigation of methodologies and emission factors for including enteric fermentation emission estimates from poultry;
- Comparison of the current CEFM with other models that estimate enteric fermentation emissions for quality assurance and verification;
- Investigation of recent research implications suggesting that certain parameters in enteric models may be simplified without significantly diminishing model accuracy; and
- Recent changes that have been implemented to the CEFM warrant an assessment of the current uncertainty analysis; therefore, a revision of the quantitative uncertainty surrounding emission estimates from this source category will be initiated. EPA plans to perform this uncertainty analysis following the completed updates to the CEFM.

EPA is continuously investigating these recommendations and potential improvements and working with USDA and other experts to utilize the best available data and methods for estimating emissions. Many of these improvements are major updates and may take multiple years to implement in full.

5.2 Manure Management (CRT Source Category 3B)

The treatment, storage, and transportation of livestock manure can produce anthropogenic CH_4 and N_2O emissions.[6] Methane is produced by the anaerobic decomposition of manure and nitrous oxide is produced from direct and indirect pathways through the processes of nitrification and denitrification; in addition, there are many underlying factors that can affect these resulting emissions from manure management, as described below.

When livestock manure is stored or treated in systems that promote anaerobic conditions (e.g., as a liquid/slurry in lagoons, ponds, tanks, or pits), the decomposition of the volatile solids component in the manure tends to produce CH_4. When manure is handled as a solid (e.g., in stacks or drylots) or deposited on pasture, range, or paddock lands, it tends to decompose aerobically and produce CO_2 and little or no CH_4. Ambient temperature, moisture, and manure storage or residency time affect the amount of CH_4 produced because they influence the growth of the bacteria responsible for CH_4 formation. For non-liquid-based manure systems, moist conditions (which are a function of rainfall and humidity) can promote CH_4 production. Manure composition, which varies by animal diet, growth rate, and animal type (particularly the different animal digestive systems), also affects the amount of CH_4 produced. In general, the greater the energy content of the feed, the greater the potential for CH_4 emissions. However, some higher-energy feeds also are more digestible than lower quality forages, which can result in less overall waste excreted from the animal.

As previously stated, N_2O emissions are produced through both direct and indirect pathways. Direct N_2O emissions are produced as part of the nitrogen (N) cycle through the nitrification and denitrification of the N in livestock dung

[6] CO_2 emissions from livestock are not estimated because annual net CO_2 emissions are assumed to be zero – the CO_2 photosynthesized by plants is returned to the atmosphere as respired CO_2 (IPCC 2006).

and urine.[7] There are two pathways for indirect N_2O emissions. The first is the result of the volatilization of N in manure (as NH_3 and NO_x) and the subsequent deposition of these gases and their products (NH_4^+ and NO_3^-) onto soils and the surface of lakes and other waters. The second pathway is the runoff and leaching of N from manure into the groundwater below, into riparian zones receiving drain or runoff water, or into the ditches, streams, rivers, and estuaries into which the land drainage water eventually flows.

The production of direct N_2O emissions from livestock manure depends on the composition of the manure (manure includes both feces and urine), the type of bacteria involved in the process, and the amount of oxygen and liquid in the manure system. For direct N_2O emissions to occur, the manure must first be handled aerobically where organic N is mineralized or decomposed to NH_4 which is then nitrified to NO_3 (producing some N_2O as a byproduct) (nitrification). Next, the manure must be handled anaerobically where the nitrate is then denitrified to N_2O and N_2 (denitrification). NO_x can also be produced during denitrification (Groffman et al. 2000; Robertson and Groffman 2015). These emissions are most likely to occur in dry manure handling systems that have aerobic conditions, but that also contain pockets of anaerobic conditions due to saturation. A very small portion of the total N excreted is expected to convert to N_2O in the waste management system (WMS).

Indirect N_2O emissions are produced when nitrogen is lost from the system through volatilization (as NH_3 or NO_x) or through runoff and leaching. The vast majority of volatilization losses from these operations are NH_3. Although there are also some small losses of NO_x, there are no quantified estimates available for use, so losses due to volatilization are only based on NH_3 loss factors. Runoff losses would be expected from operations that house animals or store manure in a manner that is exposed to weather. Runoff losses are also specific to the type of animal housed on the operation due to differences in manure characteristics. Little information is known about leaching from manure management systems as most research focuses on leaching from land application systems. However, storage systems are often designed to minimize leaching (e.g., clay soil or synthetic liners in lagoons). Since leaching losses are expected to be minimal, leaching losses are coupled with runoff losses and the runoff/leaching estimate provided in this chapter does not account for any leaching losses.

Estimates of CH_4 emissions from manure management in 2022 were 64.7 MMT CO_2 Eq. (2,312 kt); in 1990, emissions were 39.1 MMT CO_2 Eq. (1,398 kt). This represents a 65 percent increase in emissions from 1990. Emissions increased on average by 0.8 MMT CO_2 Eq. (2 percent) annually over this period. The majority of this increase is due to dairy cattle and beef cattle manure, where emissions increased 109 and 146 percent, respectively. From 2021 to 2022, there was a 3 percent decrease in total CH_4 emissions from manure management, mainly due to a decrease in swine, dairy, and beef cattle populations.

Although a large quantity of managed manure in the United States is handled as a solid, producing little CH_4, the general trend in manure management, particularly for dairy cattle and swine (which are both shifting towards larger facilities), is one of increasing use of liquid systems. Also, new regulations controlling the application of manure nutrients to land have shifted manure management practices at smaller dairies from daily spread systems to storage and management of the manure on site. In many cases, manure management systems with the most substantial methane emissions are those associated with confined animal management operations where manure is handled in liquid-based systems. Nitrous oxide emissions from manure management vary significantly between the types of management system used and can also result in indirect emissions due to other forms of nitrogen loss from the system (IPCC 2006).

While national dairy animal populations have decreased since 1990, some states have seen increases in their dairy cattle populations as the industry becomes more concentrated in certain areas of the country and the number of animals contained on each facility increases. These areas of concentration, such as California, New Mexico, and Idaho, tend to utilize more liquid-based systems to manage (flush or scrape) and store manure. Thus, the shift

[7] Direct and indirect N_2O emissions from dung and urine spread onto fields either directly as daily spread or after it is removed from manure management systems (i.e., lagoon, pit, etc.) and from livestock dung and urine deposited on pasture, range, or paddock lands are accounted for and discussed in the agricultural soil management source category within the Agriculture sector.

toward larger dairy cattle and swine facilities since 1990 has translated into an increasing use of liquid manure management systems, which have higher potential CH_4 emissions than dry systems. This significant shift in both the dairy cattle and swine industries was accounted for by incorporating state and WMS-specific CH_4 conversion factor (MCF) values in combination with the 1992, 1997, 2002, 2007, 2012, and 2017 farm-size distribution data reported in the U.S. Department of Agriculture (USDA) *Census of Agriculture* (USDA 2019d).

In 2022, total N_2O emissions from manure management were estimated to be 17.0 MMT CO_2 Eq. (64 kt); in 1990, emissions were 13.4 MMT CO_2 Eq. (50 kt). These values include both direct and indirect N_2O emissions from manure management. Nitrous oxide emissions have increased since 1990. Multiple drivers increase N_2O emissions, such as increasing nitrogen excretion rates for some animal types (see Annex, Table A-163) and increasing numbers of animals on feedlots versus other dry systems (e.g., pasture). Across the entire time series, the overall net effect is that N_2O emissions showed a 27 percent increase from 1990 to 2022, but recent declines in a few animal populations (e.g., swine and dairy cattle) resulted in a 0.9 percent decrease from 2021 to 2022.

Table 5-6 and Table 5-7 provide estimates of CH_4 and N_2O emissions from manure management by animal category.[8]

Table 5-6: CH_4 and N_2O Emissions from Manure Management (MMT CO_2 Eq.)

Gas/Animal Type	1990	2005	2018	2019	2020	2021	2022
CH_4[a]	**39.1**	**55.0**	**67.7**	**66.7**	**66.9**	**66.4**	**64.7**
Dairy Cattle	16.0	26.4	35.7	34.4	34.7	34.3	33.4
Swine	17.4	22.7	24.7	24.9	24.9	24.6	23.8
Poultry	3.8	3.4	3.0	3.1	3.0	3.0	3.0
Beef Cattle	1.8	2.2	4.2	4.1	4.2	4.4	4.3
Horses	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Sheep	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Goats	+	+	+	+	+	+	+
American Bison	+	+	+	+	+	+	+
Mules and Asses	+	+	+	+	+	+	+
N_2O[b]	**13.4**	**15.2**	**16.6**	**16.8**	**16.9**	**17.1**	**17.0**
Beef Cattle	5.2	6.0	5.9	6.0	6.1	6.4	6.4
Dairy Cattle	5.5	5.5	6.2	6.2	6.2	6.3	6.2
Swine	1.1	1.5	1.8	1.8	1.9	1.8	1.8
Poultry	1.3	1.8	2.3	2.3	2.3	2.3	2.3
Sheep	0.1	0.3	0.3	0.3	0.3	0.3	0.3
Horses	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Goats	+	+	+	+	+	+	+
Mules and Asses	+	+	+	+	+	+	+
American Bison[c]	NA	NA	NA	NA	NA	NA	NA
Total	**52.5**	**70.2**	**84.3**	**83.5**	**83.8**	**83.6**	**81.7**

+ Does not exceed 0.05 MMT CO_2 Eq.
NA (Not Available)
[a] Accounts for CH_4 reductions due to capture and destruction of CH_4 at facilities using anaerobic digesters.
[b] Includes both direct and indirect N_2O emissions.
[c] There are no American bison N_2O emissions from managed systems; American bison are maintained entirely on pasture, range, and paddock.

[8] Manure management emissions from camels are not estimated because there is no significant population of camels in the United States. Given the insignificance of estimated camel emissions in terms of the overall level and trend in national emissions, there are no immediate improvement plans to include this emissions category in the Inventory. See Annex 5 for more information on significance of estimated camel emissions.

Notes: N_2O emissions from manure deposited on pasture, range and paddock are included in the agricultural soils management category. Totals may not sum due to independent rounding.

Table 5-7: CH_4 and N_2O Emissions from Manure Management (kt)

Gas/Animal Type	1990	2005	2018	2019	2020	2021	2022
CH_4[a]	**1,398**	**1,964**	**2,418**	**2,382**	**2,390**	**2,373**	**2,312**
Dairy Cattle	572	943	1,274	1,227	1,238	1,226	1,193
Swine	621	812	882	890	888	877	851
Poultry	135	123	108	111	109	108	108
Beef Cattle	63	78	149	148	150	157	154
Horses	4	5	3	3	3	3	2
Sheep	3	2	2	2	2	2	2
Goats	+	+	+	+	+	+	+
American Bison	+	+	+	+	+	+	+
Mules and Asses	+	+	+	+	+	+	+
N_2O[b]	**50**	**57**	**63**	**63**	**64**	**65**	**64**
Beef Cattle	20	23	22	23	23	24	24
Dairy Cattle	21	21	23	23	24	24	23
Swine	4	6	7	7	7	7	7
Poultry	5	7	9	9	9	9	9
Sheep	+	1	1	1	1	1	1
Horses	+	+	+	+	+	+	+
Goats	+	+	+	+	+	+	+
Mules and Asses	+	+	+	+	+	+	+
American Bison[c]	NA	NA	NA	NA	NA	NA	NA

+ Does not exceed 0.5 kt.

NA (Not Available)

[a] Accounts for CH_4 reductions due to capture and destruction of CH_4 at facilities using anaerobic digesters.

[b] Includes both direct and indirect N_2O emissions.

[c] There are no American bison N_2O emissions from managed systems; American bison are maintained entirely on pasture, range, and paddock.

Notes: N_2O emissions from manure deposited on pasture, range and paddock are included in the agricultural soils management category. Totals by gas may not sum due to independent rounding.

Methodology and Time-Series Consistency

The methodologies presented in IPCC (2006) form the basis of the CH_4 and N_2O emission estimates for each animal type, including Tier 1, Tier 2, and use of the CEFM previously described for enteric fermentation. These methodologies use:

- IPCC (2019) Tier 1 default N_2O emission factors and MCFs for dry systems
- U.S. specific MCFs for liquid systems (ERG 2001)
- U.S. specific values for volatile solids (VS) production rate and nitrogen excretion rate for some animal types, including cattle values from the CEFM

This combination of Tier 1 and Tier 2 methods was applied to all livestock animal types and follows guidance for methodological choice presented in decision trees from the IPCC (2006). This section presents a summary of the methodologies used to estimate CH_4 and N_2O emissions from manure management.

See Annex 3.11 for more detailed information on the methodologies (including detailed formulas and emission factors), data used to calculate CH_4 and N_2O emissions, and emission results (including input variables and results at the state-level) from manure management.

Methane Calculation Methods

The following inputs were used in the calculation of manure management CH_4 emissions for 1990 through 2022:

- Animal population data (by animal type and state);
- Typical animal mass (TAM) data (by animal type);
- Portion of manure managed in each WMS, by state and animal type;
- VS production rate (by animal type and state or United States);
- Methane producing potential (B0) of the volatile solids (by animal type); and
- Methane conversion factors (MCF), the extent to which the CH_4 producing potential is realized for each type of WMS (by state and manure management system, including the impacts of any biogas collection efforts).

Methane emissions were estimated by first determining activity data, including animal population, TAM, WMS usage, and waste characteristics. The activity data sources are described below:

- Annual animal population data for 1990 through 2022 for all livestock types, except goats, horses, mules and asses, and American bison were obtained from the USDA-NASS. For cattle, the USDA populations were utilized in conjunction with birth rates, detailed feedlot placement information, and slaughter weight data to create the transition matrix in the Cattle Enteric Fermentation Model (CEFM) that models cohorts of individual animal types and their specific emission profiles. The key variables tracked for each of the cattle population categories are described in Section 5.1 and in more detail in Annex 3.10. Goat population data for 1992, 1997, 2002, 2007, 2012, and 2017; horse and mule and ass population data for 1987, 1992, 1997, 2002, 2007, 2012, and 2017; and American bison population for 2002, 2007, 2012, and 2017 were obtained from the *Census of Agriculture* (USDA 2019d). American bison population data for 1990 through 1999 were obtained from the National Bison Association (1999).
- The TAM is an annual average weight that was obtained for animal types other than cattle from information in USDA's *Agricultural Waste Management Field Handbook* (USDA 1996), the American Society of Agricultural Engineers, Standard D384.1 (ASAE 1998) and others (Meagher 1986; EPA 1992; Safley 2000; ERG 2003b; IPCC 2006; ERG 2010a). For a description of the TAM data used for cattle, see Annex 3.10.
- WMS usage was estimated for swine and dairy cattle for different farm size categories using state and regional data from USDA (USDA APHIS 1996; Bush 1998; Ott 2000; USDA 2016c) and EPA (ERG 2000a; EPA 2002a and 2002b; ERG 2018, ERG 2019). For beef cattle and poultry, manure management system usage data were not tied to farm size but were based on other data sources (ERG 2000a; USDA APHIS 2000; UEP 1999, ERG 2023). For other animal types, manure management system usage was based on previous estimates (EPA 1992). American bison WMS usage was assumed to be the same as not on feed (NOF) cattle, while mules and asses were assumed to be the same as horses.
- VS production rates for all cattle except for calves were calculated by head for each state and animal type in the CEFM. VS production rates by animal mass for all other animals were determined using data from USDA's *Agricultural Waste Management Field Handbook* (USDA 1996 and 2008; ERG 2010b and 2010c) and data that was not available in the most recent *Handbook* were obtained from the American Society of Agricultural Engineers, Standard D384.1 (ASAE 1998) or the *2006 IPCC Guidelines* (IPCC 2006). American bison VS production was assumed to be the same as NOF bulls.
- B_0 was determined for each animal type based on literature values (Morris 1976; Bryant et al. 1976; Hashimoto 1981; Hashimoto 1984; EPA 1992; Hill 1982; Hill 1984).
- MCFs for dry systems were set equal to default IPCC factors based on state climate for each year (IPCC 2019). The IPCC 2019 factors are more representative of U.S. systems and reflect the latest science. MCFs for liquid/slurry, anaerobic lagoon, and deep pit systems were calculated based on the forecast performance of biological systems relative to temperature changes as predicted in the van't Hoff-Arrhenius equation which is consistent with IPCC (2006) Tier 2 methodology.

- Data from anaerobic digestion systems with CH_4 capture and combustion were obtained from the EPA AgSTAR Program, including information available in the AgSTAR project database (EPA 2023). Anaerobic digester emissions were calculated based on estimated methane production and collection and destruction efficiency assumptions (ERG 2008).
- For all cattle except for calves, the estimated amount of VS (kg per animal-year) managed in each WMS for each animal type, state, and year were taken from the CEFM, assuming American bison VS production to be the same as NOF bulls. For animals other than cattle, the annual amount of VS (kg per year) from manure excreted in each WMS was calculated for each animal type, state, and year. This calculation multiplied the animal population (head) by the VS excretion rate (kg VS per 1,000 kg animal mass per day), the TAM (kg animal mass per head) divided by 1,000, the WMS distribution (percent), and the number of days per year (365.25).

The estimated amount of VS managed in each WMS was used to estimate the CH_4 emissions (kg CH_4 per year) from each WMS. The amount of VS (kg per year) was multiplied by the B_0 (m^3 CH_4 per kg VS), the MCF for that WMS (percent), and the density of CH_4 (kg CH_4 per m^3 CH_4). The CH_4 emissions for each WMS, state, and animal type were summed to determine the total U.S. CH_4 emissions. See details in Step 5 of Annex 3.11.

Nitrous Oxide Calculation Methods

The following inputs were used in the calculation of direct and indirect manure management N_2O emissions for 1990 through 2022:

- Animal population data (by animal type and state);
- TAM data (by animal type);
- Portion of manure managed in each WMS (by state and animal type);
- Total Kjeldahl N excretion rate (Nex);
- Direct N_2O emission factor (EF_{WMS});
- Indirect N_2O emission factor for volatilization ($EF_{volatilization}$);
- Indirect N_2O emission factor for runoff and leaching ($EF_{runoff/leach}$);
- Fraction of N loss from volatilization of NH_3 and NO_x ($Frac_{gas}$); and
- Fraction of N loss from runoff and leaching ($Frac_{runoff/leach}$).

Nitrous oxide emissions were estimated by first determining activity data, including animal population, TAM, WMS usage, and waste characteristics. The activity data sources (except for population, TAM, and WMS, which were described above) are described below:

- Nex for all cattle except for calves were calculated by head for each state and animal type in the CEFM. Nex rates by animal mass for all other animals were determined using data from USDA's *Agricultural Waste Management Field Handbook* (USDA 1996 and 2008; ERG 2010b and 2010c) and data from the American Society of Agricultural Engineers, Standard D384.1 (ASAE 1998) and IPCC (2006). American bison Nex were assumed to be the same as NOF bulls.[9]
- All N_2O emission factors (direct and indirect) were taken from IPCC (2006).
- Country-specific estimates for the fraction of N loss from volatilization ($Frac_{gas}$) and runoff and leaching ($Frac_{runoff/leach}$) were developed. $Frac_{gas}$ values were based on WMS-specific volatilization values as estimated from EPA's *National Emission Inventory - Ammonia Emissions from Animal Agriculture*

[9] Nex of American bison on grazing lands are accounted for and discussed in the agricultural soil management source category and included under pasture, range and paddock (PRP) emissions. Because American bison are maintained entirely on unmanaged WMS and N_2O emissions from unmanaged WMS are not included in the manure management source category, there are no N_2O emissions from American bison included in the manure management source category.

Operations (EPA 2005). $Frac_{runoff/leaching}$ values were based on regional cattle runoff data from EPA's Office of Water (EPA 2002b; see Annex 3.11).

To estimate N_2O emissions for cattle (except for calves), the estimated amount of N excreted (kg per animal-year) that is managed in each WMS for each animal type, state, and year were taken from the CEFM. For calves and other animals, the amount of N excreted (kg per year) in manure in each WMS for each animal type, state, and year was calculated. The population (head) for each state and animal was multiplied by TAM (kg animal mass per head) divided by 1,000, the nitrogen excretion rate (Nex, in kg N per 1,000 kg animal mass per day), WMS distribution (percent), and the number of days per year.

Direct N_2O emissions were calculated by multiplying the amount of N excreted (kg per year) in each WMS by the N_2O direct emission factor for that WMS (EF_{WMS}, in kg N_2O-N per kg N) and the conversion factor of N_2O-N to N_2O. These emissions were summed over state, animal, and WMS to determine the total direct N_2O emissions (kg of N_2O per year). See details in Step 6 of Annex 3.11.

Indirect N_2O emissions from volatilization (kg N_2O per year) were then calculated by multiplying the amount of N excreted (kg per year) in each WMS by the fraction of N lost through volatilization ($Frac_{gas}$) divided by 100, the emission factor for volatilization ($EF_{volatilization}$, in kg N_2O per kg N), and the conversion factor of N_2O-N to N_2O. Indirect N_2O emissions from runoff and leaching (kg N_2O per year) were then calculated by multiplying the amount of N excreted (kg per year) in each WMS by the fraction of N lost through runoff and leaching ($Frac_{runoff/leach}$) divided by 100, the emission factor for runoff and leaching ($EF_{runoff/leach}$, in kg N_2O per kg N), and the conversion factor of N_2O-N to N_2O. The indirect N_2O emissions from volatilization and runoff and leaching were summed to determine the total indirect N_2O emissions. See details in Step 6 of Annex 3.11.

Following these steps, direct and indirect N_2O emissions were summed to determine total N_2O emissions (kg N_2O per year) for the years 1990 to 2022.

Methodological approaches, changes to historic data, and other parameters were applied to the entire time series to ensure consistency in emissions estimates from 1990 through 2022. In some cases, the activity data source changed over the time series. For example, updated WMS distribution data were applied to 2016 for dairy cows and 2009 for swine. While previous WMS distribution data were from another data source, EPA integrated the more recent data source to reflect the best available current WMS distribution data for these animals. EPA assumed a linear interpolation distribution for years between the two data sources. Refer to Annex 3.11 for more details on data sources and methodology.

Uncertainty

An analysis (ERG 2003a) was conducted for the manure management emission estimates presented in the 1990 through 2001 *Inventory* (i.e., 2003 submission to the UNFCCC) to determine the uncertainty associated with estimating CH_4 and N_2O emissions from livestock manure management. The quantitative uncertainty analysis for this source category was performed in 2002 through the IPCC-recommended Approach 2 uncertainty estimation methodology, the Monte Carlo stochastic simulation technique. The uncertainty analysis was developed based on the methods used to estimate CH_4 and N_2O emissions from manure management systems. The series of equations used were condensed into a single equation for each animal type and state. The equations for each animal group contained four to five variables around which the uncertainty analysis was performed for each state. A normal probability distribution was assumed for all variables in the estimation equations. While there are plans to update the uncertainty to reflect recent manure management updates and forthcoming changes (see Planned Improvements, below), at this time the uncertainty estimates were directly applied to the 2022 emission estimates.

The results of the Approach 2 quantitative uncertainty analysis are summarized in Table 5-8. Manure management CH_4 emissions in 2022 were estimated to be between 53.1 and 77.7 MMT CO_2 Eq. at a 95 percent confidence level, which indicates a range of 18 percent below to 20 percent above the actual 2022 emission estimate of 64.7 MMT CO_2 Eq. At the 95 percent confidence level, N_2O emissions were estimated to be between 14.3 and 21.1 MMT CO_2

Eq. (or approximately 16 percent below and 24 percent above the actual 2022 emission estimate of 17.0 MMT CO_2 Eq.).

A quantitative uncertainty analysis for this source category was also performed using the IPCC (2006) recommended Approach 1 based on simple error propagation as well. Based on this analysis, manure management:

- CH_4 emissions in 2022 were estimated to be between 50.4 and 79.0 MMT CO_2 Eq., which indicates a range of ±21 percent above and below the 2022 emission estimate of 64.7 MMT CO_2 Eq. A ±25 percent uncertainty factor is applied to the activity data (e.g., animal populations), and a ±30 percent default uncertainty factor for Tier 1 and ±20 percent default uncertainty factor for Tier 2 is applied to the emission factors (IPCC 2006).
- N_2O emissions in 2022 were estimated to be between 11.8 and 22.2 MMT CO_2 Eq., which indicates a range of ±31 percent above and below the 2022 emission estimate of 17.0 MMT CO_2 Eq. A ±25 percent uncertainty factor is applied to the activity data (e.g., animal populations), and a ±50 percent default uncertainty factor is applied to the emission factors (IPCC 2006).
- CH_4 and N_2O emissions in 2022 were estimated to be between 66.5 and 96.9 MMT CO_2 Eq., which indicates a range of ±19 percent above and below the 2022 emission estimate of 81.7 MMT CO_2 Eq. A ±25 percent uncertainty factor is applied to the activity data (e.g., animal populations), and a ±20-50 percent default uncertainty factor is applied to the emission factors (IPCC 2006).

Table 5-8: Approach 2 Quantitative Uncertainty Estimates for CH_4 and N_2O (Direct and Indirect) Emissions from Manure Management (MMT CO_2 Eq. and Percent)

Source	Gas	2022 Emission Estimate (MMT CO_2 Eq.)	Uncertainty Range Relative to Emission Estimate[a] (MMT CO_2 Eq.)		(%)	
			Lower Bound	Upper Bound	Lower Bound	Upper Bound
Manure Management	CH_4	64.7	53.1	77.7	-18%	+20%
Manure Management	N_2O	17.0	14.3	21.1	-16%	+24%

[a] Range of emission estimates predicted by Monte Carlo stochastic simulation for a 95 percent confidence interval.

QA/QC and Verification

General (Tier 1) and category-specific (Tier 2) QA/QC activities were conducted consistent with the U.S. Inventory QA/QC plan outlined in Annex 8. Tier 2 activities focused on comparing estimates for the previous and current Inventories for N_2O emissions from managed systems and CH_4 emissions from livestock manure. All errors identified were corrected. Order of magnitude checks were also conducted, and corrections made where needed. In addition, manure N data were checked by comparing state-level data with bottom-up estimates derived at the county level and summed to the state level. Similarly, a comparison was made by animal and WMS type for the full time series, between national level estimates for N excreted, both for pasture and managed systems, and the sum of county estimates for the full time series. This was done to ensure consistency between excreted N within the manure management sector and those data provided to the managed soils sector. All errors identified were corrected.

Time-series data, including population, are validated by experts to ensure they are representative of the best available U.S.-specific data. The U.S.-specific values for TAM, Nex, VS, B_0, and MCF were also compared to the IPCC default values and validated by experts. Although significant differences exist in some instances, these differences are due to the use of U.S.-specific data and the differences in U.S. agriculture as compared to other countries. The

U.S. manure management emission estimates use the most reliable country-specific data, which are more representative of U.S. animals and systems than the IPCC (2006) default values.

For additional verification of the 1990 to 2022 estimates, the implied CH_4 emission factors for manure management (kg of CH_4 per head per year) were compared against the default IPCC (2006) values. Table 5-9 presents the implied emission factors of kg of CH_4 per head per year used for the manure management emission estimates as well as the IPCC (2006) default emission factors. The U.S. implied emission factors fall within the range of the IPCC (2006) default values, except in the case of sheep, goats, and some years for horses and dairy cattle. The U.S. implied emission factors are less than the IPCC (2006) default value for those animals due to the use of U.S.-specific data for typical animal mass and VS excretion. There is an increase in implied emission factors for dairy cattle and swine across the time series. This increase reflects the dairy cattle and swine industry trend towards larger farm sizes; large farms are more likely to manage manure as a liquid and therefore produce more CH_4 emissions. See the Recalculations for explanations for changes that affect emissions which impact these implied emission factors.

Table 5-9: IPCC (2006) Implied Emission Factor Default Values Compared with Calculated Values for CH_4 from Manure Management (kg/head/year)

Animal Type	IPCC Default CH_4 Emission Factors (kg/head/year)[a]	1990	2005	2018	2019	2020	2021	2022
Dairy Cattle	48-112	29.3	53.0	67.0	65.0	65.9	65.0	64.1
Beef Cattle	1-2	0.8	0.9	1.8	1.8	1.8	1.9	1.9
Swine	10-45	11.5	13.3	12.0	11.6	11.5	11.8	11.6
Sheep	0.19-0.37	0.3	0.4	0.4	0.4	0.4	0.4	0.4
Goats	0.13-0.26	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Poultry	0.02-1.4	0.1	0.1	0.05	0.05	0.05	0.05	0.05
Horses	1.56-3.13	1.9	1.4	1.2	1.2	1.2	1.2	1.2
American Bison	NA	0.8	0.9	0.9	0.9	0.9	0.9	0.9
Mules and Asses	0.76-1.14	0.4	0.4	0.4	0.4	0.4	0.4	0.4

NA (Not Applicable)

[a] Ranges reflect *2006 IPCC Guidelines* (Volume 4, Table 10.14) default emission factors for North America across different climate zones.

In addition, default IPCC (2006) emission factors for N_2O were compared to the U.S. *Inventory* implied N_2O emission factors. Default N_2O emission factors from the *2006 IPCC Guidelines* were used to estimate N_2O emission from each WMS in conjunction with U.S.-specific Nex values. The implied emission factors differed from the U.S. *Inventory* values due to the use of U.S.-specific Nex values and differences in populations present in each WMS throughout the time series.

Recalculations Discussion

In the previous *Inventory*, 1990 to 2020 estimates were retained from the 1990 through 2020 *Inventory*, and 2021 estimates were based on a simplified approach that used emission factors and extrapolated population estimates for all animals. For the current *Inventory*, the calculations were rerun for all years, resulting in different estimates for 2021 than the prior *Inventory*.

There were also changes to emissions resulting from activity data changes, including:

- EPA updated the WMS distributions for broilers, layers, and beef feedlot animal types. For broilers, this affected 1993 through 2021, for layers 2000 through 2021, and for beef feedlots all years of the time series (ERG 2023).

- EPA updated the calf TAM values to coincide with values used within the CEFM. This affected all years of the time series.
- EPA updated the solid storage direct N_2O emission factor to the updated guidance provided in IPCC (2019).
- EPA updated how poultry digesters were applied, splitting other poultry and caged layers (previously done for broilers) as well as the year for which select swine anaerobic digesters were shutdown per notes provided in AgSTAR.
- EPA discovered and corrected an error within the CEFM (see NIR section 5.1 and annex 3.10) related to the urinary energy input used for feedlot cattle, which affected VS results for this animal group. The urinary energy default was updated from 0.04 to 0.02 for feedlot cattle.

The cumulative effect of all these recalculations had a minor impact on the overall manure management emissions estimates:

- CH_4 emissions increased an average 0.6 percent over the time series, with the largest decrease of 0.2 percent (0.1 MMT CO_2 Eq) in 2002 to the largest increase of 1.8 percent (1.2 MMT CO_2 Eq.) in 2017.
- N_2O emissions increased an average 3.4 percent over the time series, with the largest decrease of 3.6 percent (0.6 MMT CO_2 Eq.) in 2020 and the largest increase of 7.8 percent (1.0 MMT CO_2 Eq.) in 1990.
- Over the time series the average total emissions increased by 1.2 percent from the previous *Inventory*. The changes ranged from the largest decrease 0.5 percent (0.4 MMT CO_2 Eq.) in 2020, to the largest increase 2.1 percent (1.1 MMT CO_2 Eq.) in 1990.

Planned Improvements

Regular annual data reviews and updates are necessary to maintain an emissions inventory that reflects the current base of knowledge. In addition to the documented approaches currently used to address data availability, EPA conducts data assessments to pursue a number of potential improvements.

Potential improvements (long-term improvements) for future *Inventory* years include:

- Providing supplemental details on CH_4 emissions reductions due to the use of anaerobic digesters (the *Inventory* currently estimates only emissions from anaerobic digestion systems).
- Investigating the updated IPCC *2019 Refinement* default N_2O emissions factor for anaerobic digesters. Historically, EPA has not estimated N_2O emissions from digesters as the default guidance was no emissions. Incorporating AgSTAR data for N_2O emissions, like CH_4 emissions, is a longer-term goal for EPA.
- Investigating updates to the current anaerobic digester MCFs based on IPCC (2019).

EPA is aware of the following potential updates or improvements but notes that implementation will be based on available resources and data availability:

- Updating the B_0 data used in the *Inventory*, as data become available. EPA is conducting outreach with counterparts from USDA as to available data and research on B_0.
- Comparing CH_4 and N_2O emission estimates with estimates from other models and more recent studies and compare the results to the *Inventory*.
- Comparing manure management emission estimates with on-farm measurement data to identify opportunities for improved estimates.
- Comparing VS and Nex data to literature data to identify opportunities for improved estimates.

- Determining if there are revisions to the U.S.-specific method for calculating liquid systems for MCFs based on updated guidance from the IPCC *2019 Refinement*. EPA previously began this investigation to determine the potential differences between the methods.
- Investigating improved emissions estimate methodologies for swine pit systems with less than one month of storage (the updated swine WMS data included this WMS category).
- Improving the linkages with the Enteric Fermentation source category estimates. For future Inventories, it may be beneficial to have the CEFM and Manure Management calculations in the same model, as they rely on much of the same activity data and on each other's outputs to properly calculate emissions. EPA has begun this investigation and plans to develop a model to calculate emissions for these two categories.
- Continuing to investigate new sources of WMS data. EPA is collaborating with the USDA to collect or use existing survey data for potential improvements to the *Inventory*.
- Revising the uncertainty analysis to address changes that have been implemented to the CH_4 and N_2O estimates. The plan is to align the timing of the updated Manure Management uncertainty analysis with the uncertainty analysis for Enteric Fermentation.

5.3 Rice Cultivation (CRT Source Category 3C)

Most of the world's rice is grown on flooded fields (Baicich 2013) that create anaerobic conditions leading to CH_4 production through a process known as methanogenesis. Approximately 60 to 90 percent of the CH_4 produced by methanogenic bacteria in flooded rice fields is oxidized in the soil and converted to CO_2 by methanotrophic bacteria. The remainder is emitted to the atmosphere (Holzapfel-Pschorn et al. 1985; Sass et al. 1990) or transported as dissolved CH_4 into groundwater and waterways (Neue et al. 1997). Methane is transported to the atmosphere primarily through the rice plants, but some CH_4 also escapes via ebullition (i.e., bubbling through the water) and to a much lesser extent by diffusion through the water (van Bodegom et al. 2001).

Water management is arguably the most important factor affecting CH_4 emissions in rice cultivation, and improved water management has the largest potential to mitigate emissions (Yan et al. 2009). Upland rice fields are not flooded, and therefore do not produce CH_4, but large amounts of CH_4 can be emitted in continuously irrigated fields, which is the most common practice in the United States (USDA 2012). Single or multiple aeration events with drainage of a field during the growing season can significantly reduce these emissions (Wassmann et al. 2000a), but drainage may also increase N_2O emissions. Deepwater rice fields (i.e., fields with flooding depths greater than one meter, such as natural wetlands) tend to have fewer living stems reaching the soil, thus reducing the amount of CH_4 transport to the atmosphere through the plant compared to shallow-flooded systems (Sass 2001).

Other management practices also influence CH_4 emissions from flooded rice fields including rice residue straw management and application of organic amendments, in addition to cultivar selection due to differences in the amount of root exudates[10] among rice varieties (Neue et al. 1997). These practices influence the amount of organic matter available for methanogenesis, and some practices, such as mulching rice straw or composting organic amendments, can reduce the amount of labile carbon and limit CH_4 emissions (Wassmann et al. 2000b).

[10] The roots of rice plants add organic material to the soil through a process called "root exudation." Root exudation is thought to enhance decomposition of the soil organic matter and release nutrients that the plant can absorb for production. The amount of root exudate produced by a rice plant over a growing season varies among rice varieties.

Fertilization practices also influence CH_4 emissions, particularly the use of fertilizers with sulfate, which can reduce CH_4 emissions (Wassmann et al. 2000b; Linquist et al. 2012). Other environmental variables also impact the methanogenesis process such as soil temperature and soil type. Soil temperature regulates the activity of methanogenic bacteria, which in turn affects the rate of CH_4 production. Soil texture influences decomposition of soil organic matter but is also thought to have an impact on oxidation of CH_4 in the soil (Sass et al. 1994).

Rice is currently cultivated in 12 states, including Arkansas, California, Florida, Illinois, Kentucky, Louisiana, Minnesota, Mississippi, Missouri, New York, Tennessee, and Texas. Soil types, rice varieties, and cultivation practices vary across the United States, but most farmers apply fertilizers and do not harvest crop residues. In addition, a second, ratoon rice crop is sometimes grown in the Southeastern region of the country. Ratoon crops are produced from regrowth of the stubble remaining after the harvest of the first rice crop. Methane emissions from ratoon crops are higher than those from the primary crops due to the increased amount of labile organic matter available for anaerobic decomposition in the form of relatively fresh crop residue straw. Emissions tend to be higher in rice fields if the residues have been in the field for less than 30 days before planting the next rice crop (Lindau and Bollich 1993; IPCC 2006; Wang et al. 2013).

A combination of Tier 1 and 3 methods are used to estimate CH_4 emissions from rice cultivation across most of the time series, while a surrogate data method has been applied to estimate national emissions for 2021 to 2022 in this *Inventory* due to lack of data in these years of the time series. National emission estimates based on surrogate data will be recalculated in a future *Inventory* with the Tier 1 and 3 methods as data becomes available.

Overall, rice cultivation is a minor source of CH_4 emissions in the United States relative to other source categories (see Table 5-10, Table 5-11, and Figure 5-3). Most emissions occur in Arkansas, California, Louisiana, Mississippi, Missouri, and Texas. In 2022, CH_4 emissions from rice cultivation were 18.9 MMT CO_2 Eq. (674 kt CH_4). Annual emissions fluctuated between 1990 and 2022, which is largely due to differences in the amount of rice harvested areas over time. There has been a marginal decrease in emissions since 1990. Interestingly, the estimated emissions in 2022 are roughly the same as emissions in 1990.

Table 5-10: CH_4 Emissions from Rice Cultivation (MMT CO_2 Eq.)

State	1990	2005	2018	2019	2020	2021	2022
Arkansas	6.3	8.8	8.0	5.6	6.8	NE	NE
California	3.2	3.4	3.7	3.5	3.6	NE	NE
Florida	+	+	+	+	+	NE	NE
Illinois	+	+	+	+	+	NE	NE
Kentucky	+	+	+	+	+	NE	NE
Louisiana	3.5	3.8	3.7	3.2	3.7	NE	NE
Minnesota	+	+	+	+	+	NE	NE
Mississippi	1.1	1.3	0.7	0.6	0.6	NE	NE
Missouri	0.5	1.2	1.2	0.9	1.0	NE	NE
New York	+	+	+	+	+	NE	NE
Tennessee	+	+	+	+	+	NE	NE
Texas	4.3	1.9	2.6	1.9	2.9	NE	NE
Total	**18.9**	**20.6**	**19.9**	**15.6**	**18.6**	**18.3**	**18.9**

+ Does not exceed 0.05 MMT CO_2 Eq.

NE (Not Estimated). State-level emissions are not estimated for 2021 through 2022 in this *Inventory*. A surrogate method is used to estimate emissions for these years only at the national scale.

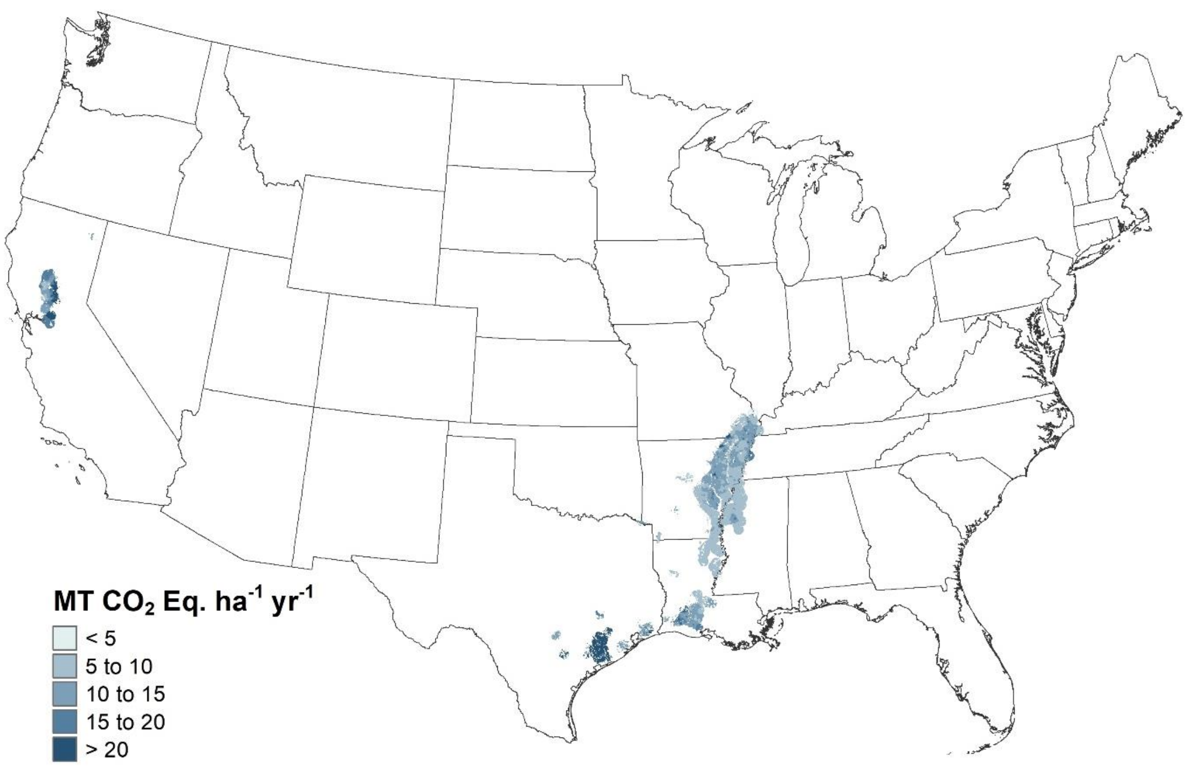
Note: Totals may not sum due to independent rounding.

Table 5-11: CH_4 Emissions from Rice Cultivation (kt CH_4)

State	1990	2005	2018	2019	2020	2021	2022
Arkansas	224.2	315.5	287.1	200.5	243.4	NE	NE
California	114.5	122.8	131.5	123.9	129.1	NE	NE
Florida	+	1.2	+	+	+	NE	NE
Illinois	+	0.4	0.1	+	0.1	NE	NE
Kentucky	+	+	+	+	+	NE	NE
Louisiana	124.9	135.0	131.4	113.7	130.4	NE	NE
Minnesota	1.0	1.7	+	0.8	+	NE	NE
Mississippi	39.0	46.5	24.3	20.3	21.5	NE	NE
Missouri	19.5	42.7	43.0	31.8	34.4	NE	NE
New York	0.2	+	+	+	+	NE	NE
Tennessee	+	0.1	+	+	+	NE	NE
Texas	153.5	69.5	93.6	67.0	104.7	NE	NE
Total	**677**	**735**	**711**	**558**	**664**	**653**	**674**

+ Does not exceed 0.5 kt.
NE (Not Estimated). State-level emissions are not estimated for 2021 through 2022 in this *Inventory*. A surrogate method is used to estimate emissions for these years only at the national scale.
Note: Totals may not sum due to independent rounding.

Figure 5-3: Annual CH_4 Emissions from Rice Cultivation, 2020, Using the Tier 3 DayCent Model



Note: Only national-scale emissions are estimated for 2021 and 2022 in this *Inventory* using a surrogate data method described in the Methodology section; therefore, the fine-scale emission patterns in this map are based on the estimates for 2020.

Methodology and Time-Series Consistency

The methodology used to estimate CH_4 emissions from rice cultivation is based on a combination of IPCC Tier 1 and 3 approaches. The Tier 3 method utilizes the DayCent process-based model to estimate CH_4 emissions from rice cultivation (Cheng et al. 2013) and has been tested in the United States (see Annex 3.12) and Asia (Cheng et al. 2013, 2014). The model simulates hydrological conditions and thermal regimes, organic matter decomposition, root exudation, rice plant growth and its influence on oxidation of CH_4, as well as CH_4 transport through the plant and via ebullition (Cheng et al. 2013). The method captures the influence of organic amendments and rice straw management on methanogenesis in the flooded soils, and ratooning of rice crops with a second harvest during the growing season. In addition to CH_4 emissions, DayCent simulates soil carbon stock changes and N_2O emissions (Parton et al. 1987 and 1998; Del Grosso et al. 2010) and allows for a seamless set of simulations for crop rotations that include both rice and non-rice crops.

The Tier 1 method is applied to estimate CH_4 emissions from rice when grown in rotation with crops that are not simulated by DayCent, such as vegetable crops. The Tier 1 method is also used for areas converted between agriculture (i.e., cropland and grassland) and other land uses, such as forest land, wetland, and settlements. In addition, the Tier 1 method is used to estimate CH_4 emissions from organic soils (i.e., Histosols) and from areas with very gravelly, cobbly, or shaley soils (greater than 35 percent by volume). The Tier 3 method using DayCent has not been fully tested for estimating emissions associated with these conditions.

The Tier 1 method for estimating CH_4 emissions from rice production utilizes a default base emission rate and scaling factors (IPCC 2006). The base emission rate represents emissions for continuously flooded fields with no organic amendments. Scaling factors are used to adjust the base emission rate for water management and organic amendments that differ from continuous flooding with no organic amendments. The method accounts for pre-season and growing season flooding; types and amounts of organic amendments; and the number of rice production seasons within a single year (i.e., single cropping and double-cropping with ratooning). The Tier 1 analysis is implemented in the Agriculture and Land Use National Greenhouse Gas Inventory (ALU) software (Ogle et al. 2016).[11]

Rice cultivation areas are based on crop and land use histories recorded in the USDA National Resources Inventory (NRI) survey (USDA-NRCS 2020) and extended through 2020 using the USDA-NASS Crop Data Layer Product (USDA-NASS 2021, Johnson and Mueller 2010). The areas have been modified in the original NRI survey through a process in which the Forest Inventory and Analysis (FIA) survey data and the National Land Cover Dataset (Yang et al. 2018) are harmonized with the NRI data (Nelson et al. 2020). This process ensures that the land use areas are consistent across all land use categories (See Section 6.1, Representation of the U.S. Land Base for more information).

The NRI is a statistically based sample of all non-federal land and includes approximately 604,000 survey locations in agricultural cropland and grassland for the conterminous United States and Hawaii of which 7,888 include one or more years of rice cultivation. The Tier 3 method is used to estimate CH_4 emissions from 5,998 of the NRI survey locations, and the remaining 1,890 survey locations are estimated with the Tier 1 method. Each NRI survey location is associated with a survey weight that allows scaling of CH_4 emission to the entire land base with rice cultivation (i.e., each weight approximates the amount of area with the same land-use/management history as the survey location). Land-use and some management information in the NRI (e.g., crop type, soil attributes, and irrigation) were collected on a 5-year cycle beginning in 1982, along with cropping rotation data in four out of five years for each five-year time period (i.e., 1979 to 1982, 1984 to 1987, 1989 to 1992, and 1994 to 1997). The NRI program began collecting annual data in 1998, with data through 2017 (USDA-NRCS 2020). For 2018-2020, the time series is extended with the crop data provided in USDA-NASS CDL (USDA-NASS 2021). CDL data have a 30 to 58 m spatial resolution, depending on the year. NRI survey locations are overlaid on the CDL in a geographic information

[11] See http://www.nrel.colostate.edu/projects/ALUsoftware/.

system, and the crop types are extracted to extend the cropping histories. The harvested rice areas in each state are presented in Table 5-12.

Table 5-12: Rice Area Harvested (1,000 Hectares)

State/Crop	1990	2005	2018	2019	2020	2021	2022
Arkansas	611	782	659	512	663	NE	NE
California	251	237	226	218	224	NE	NE
Florida	0	3	0	0	0	NE	NE
Illinois	0	1	0	0	1	NE	NE
Kentucky	0	0	0	0	0	NE	NE
Louisiana	399	400	356	313	383	NE	NE
Minnesota	3	6	0	3	0	NE	NE
Mississippi	177	191	98	96	109	NE	NE
Missouri	48	96	99	74	85	NE	NE
New York	1	0	0	0	0	NE	NE
Tennessee	0	1	0	0	0	NE	NE
Texas	294	104	164	119	167	NE	NE
Total	**1,784**	**1,823**	**1,603**	**1,335**	**1,633**	**NE**	**NE**

NE (Not Estimated). Area data will be updated in the next *Inventory*.
Note: Totals may not sum due to independent rounding.

The Southeastern states have sufficient growing periods for a ratoon crop in some years (Table 5-13). For example, the growing season length is occasionally sufficient for ratoon crops to be grown on about two percent of the rice fields in Arkansas. No data are available about ratoon crops in Missouri or Mississippi, so the average amount of ratooning in Arkansas was assigned to these states. Ratoon cropping occurs much more frequently in Louisiana (LSU 2015 for years 2000 through 2013, 2015) and Texas (TAMU 2015 for years 1993 through 2015), averaging 32 percent and 45 percent of rice acres planted, respectively. Florida also has a large fraction of area with a ratoon crop (49 percent). Ratoon rice crops are not grown in California. Ratooning practices are assigned to individual NRI locations using a hot-deck imputation method with six complete imputations for each NRI location to address uncertainty. The method is based on random assignment of ratooning to approximate the percentages of fields managed with ratooning provided in Table 5-14.

Table 5-13: Average Ratooned Area as Percent of Primary Growth Area (Percent)

State	1990-2015
Arkansas[a]	1.9%
California	0%
Florida[b]	45.2%
Louisiana[c]	39.5%
Mississippi[a]	37.8%
Missouri[a]	2.4%
Texas[d]	49.5%

[a] Arkansas: *1990–2000* (Slaton 1999 through 2001); *2001–2011* (Wilson 2002 through 2007, 2009 through 2012); *2012–2013* (Hardke 2013, 2014). Estimates of ratooning for Missouri and Mississippi are based on the data from Arkansas.
[b] Florida - Ratoon: *1990–2000* (Schueneman 1997, 1999 through 2001); *2001* (Deren 2002); *2002–2003* (Kirstein 2003 through 2004, 2006); *2004* (Cantens 2004 through 2005); *2005–2013* (Gonzalez 2007 through 2014).
[c] Louisiana: *1990–2013* (Linscombe 1999, 2001 through 2014).
[d] Texas: *1990–2002* (Klosterboer 1997, 1999 through 2003); *2003–2004* (Stansel 2004 through 2005); *2005* (Texas Agricultural Experiment Station 2006); *2006–2013* (Texas Agricultural Experiment Station 2007 through 2014).

While rice crop production in the United States includes a minor amount of land with mid-season drainage or alternate wet-dry periods, the majority of rice growers use continuously flooded water management systems (Hardke 2015; UCCE 2015; Hollier 1999; Way et al. 2014). Therefore, continuous flooding was assumed in the DayCent simulations and the Tier 1 analysis. Variation in flooding can be incorporated in future inventories if updated water management data are available.

Winter flooding is another key practice associated with water management in rice fields, and the impact of winter flooding on CH_4 emissions is addressed in the Tier 3 and Tier 1 analyses. Flooding is used to prepare fields for the next growing season, and to create waterfowl habitat (Young 2013; Miller et al. 2010; Fleskes et al. 2005). Fitzgerald et al. (2000) suggests that as much as 50 percent of the annual emissions may occur during winter flooding. Winter flooding is a common practice with an average of 34 percent of fields managed with winter flooding in California (Miller et al. 2010; Fleskes et al. 2005), and approximately 21 percent of the fields managed with winter flooding in Arkansas (Wilson and Branson 2005 and 2006; Wilson and Runsick 2007 and 2008; Wilson et al. 2009 and 2010; Hardke and Wilson 2013 and 2014; Hardke 2015). No data are available on winter flooding for Texas, Louisiana, Florida, Missouri, or Mississippi. For these states, the average amount of flooding is assumed to be similar to Arkansas. In addition, the amount of flooding is assumed to be relatively constant over the *Inventory* time series. Similar to ratooning practices, winter flooding is assigned to individual NRI locations using a hot-deck imputation method with six complete imputations for each NRI location to address uncertainty. The method is based on random assignment of winter flooding to approximate the percentages of fields managed with winter flooding as discussed above.

A data splicing method is used to estimate emissions from 2021 to 2022 associated with the rice CH_4 emissions for Tier 1 and 3 methods. Specifically, a linear regression model with autoregressive moving average (ARMA) errors was used to estimate the relationship between the surrogate data and emissions data from 1990 through 2020, which were derived using the Tier 3 methods (Brockwell and Davis 2016). Surrogate data are based on rice commodity statistics from USDA-NASS.[12] See Box 5-2 for more information about the surrogate data method. For the Tier 1 method, a linear-time series model is used to estimate emissions for 2021 to 2022 without surrogate data.

Box 5-2: Surrogate Data Method

An approach to extend the time series is needed to estimate emissions from rice cultivation because there are gaps in activity data at the end of the time series. This is mainly because the National Resources Inventory (NRI) does not release data every year, and the NRI is a key data source for estimating greenhouse gas emissions.

A surrogate data method has been selected to impute missing emissions at the end of the time series. A linear regression model with autoregressive moving average (ARMA) errors (Brockwell and Davis 2016) is used to estimate the relationship between the surrogate data and the observed 1990 to 2020 emissions data that has been compiled using the inventory methods described in this section. The model to extend the time series is given by

$$Y = X\beta + \varepsilon,$$

where Y is the response variable (e.g., CH_4 emissions), $X\beta$ is the surrogate data that is used to predict the missing emissions data, and ε is the remaining unexplained error. Models with a variety of surrogate data were tested, including commodity statistics, weather data, or other relevant information. Parameters are estimated from the observed data for 1990 to 2020 using standard statistical techniques, and these estimates are used to predict the missing emissions data for 2021 to 2022.

A critical issue in using splicing methods is to adequately account for the additional uncertainty introduced by predicting emissions with related information without compiling the full inventory. For example, predicting CH_4 emissions will increase the total variation in the emission estimates for these specific years, compared to those years in which the full inventory is compiled. This added uncertainty is quantified within the model framework using a Monte Carlo approach. The approach requires estimating parameters for results in each Monte Carlo simulation for the full inventory (i.e., the surrogate data model is refit with the emissions estimated in each Monte Carlo iteration from the full inventory analysis with data from 1990 to 2020).

[12] See https://quickstats.nass.usda.gov/.

In order to ensure time-series consistency, the same methods are applied from 1990 to 2020, and data splicing methods are used to approximate emissions for the remainder of the 2021 to 2022 time series based on the emissions data from 1990 to 2020. The surrogate data method and linear time series approach, used for the Tier 3 and 1 methods, respectively, are consistent with data splicing methods in IPCC (2006).

Uncertainty

Sources of uncertainty in the Tier 3 method include management practices, uncertainties in model structure (i.e., algorithms and parameterization), and variance associated with the NRI sample. Sources of uncertainty in the IPCC (2006) Tier 1 method include the emission factors, management practices, and variance associated with the NRI sample. The total uncertainty was quantified with two variance components (Ogle et al. 2010) that are combined using simple error propagation methods provided by the IPCC (2006), i.e., by taking the square root of the sum of the squares of the standard deviations of the uncertain quantities. For the first variance component, a Monte Carlo analysis was used to propagate uncertainties in the Tier 1 and 3 methods for the management data, as well as emission factors and model structure/parameterization, respectively. The second variance component is quantifying uncertainty in scaling from the NRI survey to the entire area of rice cultivation, and is computed using a standard variance estimator for a two-stage sample design (Särndal et al. 1992). For 2021 to 2022, there is additional uncertainty propagated through the Monte Carlo analysis associated with the surrogate data method (See Box 5-2 for information about propagating uncertainty with the surrogate data method). The uncertainties from the Tier 1 and 3 approaches are combined to produce the final CH_4 emissions estimate using simple error propagation (IPCC 2006). Additional details on the uncertainty methods are provided in Annex 3.12.

Rice cultivation CH_4 emissions in 2022 were estimated to be between 5.1 and 32.6 MMT CO_2 Eq. at a 95 percent confidence level, which indicates a range of 73 percent below to 73 percent above the 2022 emission estimate of 18.9 MMT CO_2 Eq. (see Table 5-14).

Table 5-14: Approach 2 Quantitative Uncertainty Estimates for CH_4 Emissions from Rice Cultivation (MMT CO_2 Eq. and Percent)

Source	Inventory Method	Gas	2022 Emission Estimate (MMT CO_2 Eq.)	Uncertainty Range Relative to Emission Estimate[a] (MMT CO_2 Eq.)		(%)	
				Lower Bound	Upper Bound	Lower Bound	Upper Bound
Rice Cultivation	Tier 3	CH_4	15.9	2.2	29.6	-86%	+86%
Rice Cultivation	Tier 1	CH_4	3.0	2.0	4.0	-34%	+34%
Rice Cultivation	**Total**	**CH_4**	**18.9**	**5.1**	**32.6**	**-73%**	**+73%**

[a] Range of emission estimates is the 95 percent confidence interval.

QA/QC and Verification

General (Tier 1) and category-specific (Tier 2) QA/QC activities were conducted consistent with the U.S. Inventory QA/QC plan outlined in Annex 8. Quality control measures include checking input data, model scripts, and results to ensure data are properly handled throughout the inventory process. Inventory reporting forms and text are reviewed and revised as needed to correct transcription errors.

Model results are compared to field measurements to verify that results adequately represent CH_4 emissions. The comparisons included over 17 long-term experiments, representing about 238 combinations of management treatments across all the sites. A statistical relationship was developed to assess uncertainties in the model structure and parameterization, adjusting the estimates for model bias and assessing precision in the resulting estimates (methods are described in Ogle et al. 2007). See Annex 3.12 for more information.

Recalculations Discussion

Several improvements have been implemented in this *Inventory* leading to recalculations, including a) updated time series of land representation data that identifies which points and years were sown with rice (Nelson et al 2020), b) extending the time-series of crop history with CDL data, c) imputing ratooning and winter flooding onto individual NRI survey points, d) updated fertilizer and organic amendment additions, and e) revisions to the approach for assigning organic matter amendments and crop residue inputs. As a result of these changes, CO_2-equivalent emissions changed annually with an average annual increase of 0.97 MMT CO_2 Eq., or 5.5 percent, over the time series from 1990 to 2021 compared to the previous *Inventory*.

Planned Improvements

A key planned improvement for rice cultivation is to refine the model algorithms and re-calibration of the Tier 3 DayCent model using the latest observational data from experiments. Another improvement is collection of more information about water management and refinement of the application to incorporate mid-season drainage and alternate wetting and drying systems. Improvements are expected to be completed for the next *Inventory* (i.e., 2025 submission to the UNFCCC, 1990 through 2023 *Inventory*), pending prioritization of resources.

5.4 Agricultural Soil Management (CRT Source Category 3D)

Nitrous oxide is naturally produced in soils through the microbial processes of nitrification and denitrification that is driven by the availability of mineral nitrogen (N) (Firestone and Davidson 1989).[13] Mineral nitrogen is made available in soils through decomposition of soil organic matter and plant litter, as well as asymbiotic fixation of nitrogen from the atmosphere.[14] Several agricultural activities increase mineral nitrogen availability in soils that lead to direct N_2O emissions at the site of a management activity (see Figure 5-4) (Mosier et al. 1998). These activities include synthetic nitrogen fertilization; application of managed livestock manure; application of other organic materials such as biosolids (i.e., treated sewage sludge); deposition of manure on soils by domesticated animals in pastures, range, and paddocks (PRP) (i.e., unmanaged manure); retention of crop residues (nitrogen-fixing legumes and non-legume crops and forages); and drainage of organic soils[15] (i.e., Histosols) (IPCC 2006). Additionally, agricultural soil management activities, including irrigation, drainage, tillage practices, cover crops, and fallowing of land, can influence nitrogen mineralization from soil organic matter and levels of asymbiotic nitrogen fixation. Indirect emissions of N_2O occur when nitrogen is transported from a site and is subsequently converted to N_2O; there are two pathways for indirect emissions: (1) volatilization and subsequent atmospheric deposition of applied/mineralized nitrogen, and (2) surface runoff and leaching of applied/mineralized nitrogen

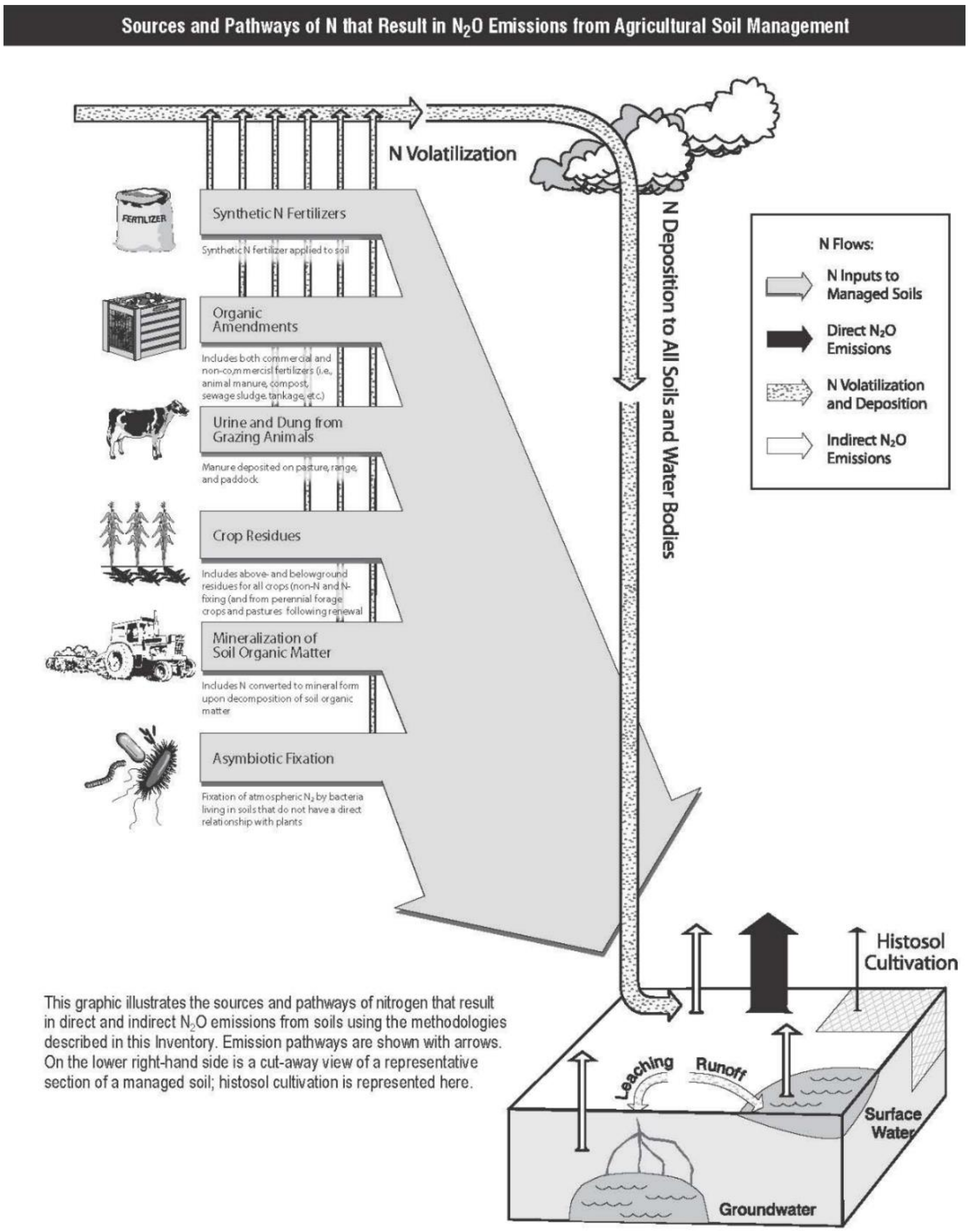
[13] Nitrification and denitrification are driven by the activity of microorganisms in soils. Nitrification is the aerobic microbial oxidation of ammonium (NH_4^+) to nitrate (NO_3^-), and denitrification is the anaerobic microbial reduction of nitrate to N_2. Nitrous oxide is a gaseous intermediate product in the reaction sequence of nitrification and denitrification.

[14] Asymbiotic nitrogen fixation is the fixation of atmospheric N_2 by bacteria living in soils that do not have a direct relationship with plants.

[15] Drainage of organic soils in former wetlands enhances mineralization of nitrogen-rich organic matter, thereby increasing N_2O emissions from these soils.

into groundwater and surface water.[16] Direct and indirect emissions from agricultural lands are included in this section (i.e., cropland and grassland as defined in Section 6.1). Nitrous oxide emissions from forest land and settlements soils are found in Sections 6.2 and 6.10, respectively.

Figure 5-4: Sources and Pathways of Nitrogen that Result in N_2O Emissions from Agricultural Soil Management



[16] These processes entail volatilization of applied or mineralized nitrogen as NH_3 and NO_x, transformation of these gases in the atmosphere (or upon deposition), and deposition of the nitrogen primarily in the form of particulate NH_4^+, nitric acid (HNO_3), and NO_x. In addition, hydrological processes lead to leaching and runoff of NO_3^- that is converted to N_2O in aquatic systems, e.g., wetlands, rivers, streams and lakes. Note: N_2O emissions are not estimated for aquatic systems associated with nitrogen inputs from terrestrial systems in order to avoid double-counting.

Agricultural soils produce the majority of N_2O emissions in the United States. Estimated emissions in 2022 are 290.8 MMT CO_2 Eq. (1,097 kt) (see Table 5-15 and Table 5-16). Annual N_2O emissions from agricultural soils are 3.2 percent greater in 2022 compared to 1990, but emissions fluctuated between 1990 and 2022 due to inter-annual variability largely associated with weather patterns, synthetic fertilizer use, and crop production. From 1990 to 2022, cropland accounted for 68 percent of total direct emissions on average from agricultural soil management, while grassland accounted for 32 percent. On average, 79 percent of indirect emissions are from croplands and 21 percent from grasslands. Estimated direct and indirect N_2O emissions by sub-source category are shown in Table 5-17 and Table 5-18.

Table 5-15: N_2O Emissions from Agricultural Soils (MMT CO_2 Eq.)

Activity	1990	2005	2018	2019	2020	2021	2022
Direct	**258.8**	**265.6**	**298.3**	**280.9**	**262.8**	**267.7**	**262.5**
Cropland	174.9	180.6	208.9	193.4	182.4	184.3	180.3
Grassland	83.9	85.1	89.4	87.5	80.3	83.4	82.1
Indirect	**29.9**	**28.4**	**35.1**	**34.7**	**29.4**	**30.3**	**28.3**
Cropland	23.6	22.3	28.1	28.0	23.3	24.1	22.2
Grassland	6.4	6.1	7.0	6.8	6.1	6.2	6.1
Total	**288.8**	**294.1**	**333.4**	**315.6**	**292.1**	**298.0**	**290.8**

Notes: Estimates for 2021 to 2022 are based on a data splicing method, except for other organic nitrogen amendments that are based on a data splicing method for 2018 to 2022 (see Methodology section). Totals may not sum due to independent rounding.

Table 5-16: N_2O Emissions from Agricultural Soils (kt N_2O)

Activity	1990	2005	2018	2019	2020	2021	2022
Direct	**977**	**1,002**	**1,126**	**1,060**	**992**	**1,010**	**990**
Cropland	660.0	681.4	788.3	729.9	688.5	695.4	680.6
Grassland	316.7	321.1	337.4	330.0	303.1	314.6	309.9
Indirect	**113**	**107**	**133**	**131**	**111**	**114**	**107**
Cropland	89.0	84.2	106.2	105.6	88.0	91.1	83.9
Grassland	24.0	23.1	26.4	25.5	22.9	23.3	22.9
Total	**1,090**	**1,110**	**1,258**	**1,191**	**1,102**	**1,124**	**1,097**

Notes: Estimates for 2021 to 2022 are based on a data splicing method, except for other organic nitrogen amendments that are based on a data splicing method for 2018 to 2022 (see Methodology section). Totals may not sum due to independent rounding.

Table 5-17: Direct N_2O Emissions from Agricultural Soils by Land Use Type and Nitrogen Input Type (MMT CO_2 Eq.)

Activity	1990	2005	2018	2019	2020	2021	2022
Cropland	**174.9**	**180.6**	**208.9**	**193.4**	**182.4**	**184.3**	**180.3**
Mineral Soils	**171.5**	**177.3**	**205.9**	**190.5**	**179.5**	**181.4**	**177.4**
Synthetic Fertilizer	61.0	64.3	70.3	65.7	63.2	63.4	62.0
Organic Amendment[a]	11.5	12.7	14.7	14.6	14.4	14.7	14.6
Residue N[b]	34.1	35.0	39.6	34.5	37.6	33.2	32.4
Mineralization and Asymbiotic Fixation	64.8	65.3	81.3	75.7	64.3	70.1	68.4
Drained Organic Soils	3.4	3.2	3.0	2.9	2.9	2.9	2.9
Grassland	**83.9**	**85.1**	**89.4**	**87.5**	**80.3**	**83.4**	**82.1**
Mineral Soils	**81.6**	**82.8**	**87.2**	**85.2**	**78.1**	**81.1**	**79.8**
Synthetic Fertilizer	+	+	+	+	+	+	+
PRP Manure	15.4	14.2	14.0	13.6	13.3	13.9	13.8
Managed Manure[c]	+	+	+	+	+	+	+

Biosolids (i.e., treated Sewage Sludge)	0.2	0.4	0.4	0.4	0.4	0.4	0.4
Residue N[d]	27.1	28.4	28.0	28.3	28.2	26.3	25.9
Mineralization and Asymbiotic Fixation	38.9	39.8	44.8	42.9	36.2	40.5	39.8
Drained Organic Soils	2.3	2.2	2.2	2.2	2.2	2.3	2.3
Total	**258.8**	**265.6**	**298.3**	**280.9**	**262.8**	**267.7**	**262.5**

+ Does not exceed 0.05 MMT CO_2 Eq.

[a] Organic amendment inputs include managed manure, daily spread manure, and commercial organic fertilizers (i.e., dried blood, dried manure, tankage, compost, and other).

[b] Cropland residue nitrogen inputs include nitrogen in unharvested cover crops as well as harvested crops.

[c] Managed manure inputs include managed manure and daily spread manure amendments that are applied to grassland soils.

[d] Grassland residue nitrogen inputs include residual biomass, both legumes and grasses, that is ungrazed and becomes dead organic matter.

Notes: Estimates for 2021 to 2022 are based on a data splicing method, except for other organic nitrogen amendments that are based on a data splicing method for 2018 to 2022 (see Methodology section). Totals may not sum due to independent rounding.

Table 5-18: Indirect N_2O Emissions from Agricultural Soils (MMT CO_2 Eq.)

Activity	1990	2005	2018	2019	2020	2021	2022
Cropland	**23.6**	**22.3**	**28.1**	**28.0**	**23.3**	**24.1**	**22.2**
Volatilization & Atm. Deposition	6.6	7.0	7.9	7.1	7.5	7.4	7.3
Surface Leaching & Run-Off	17.0	15.3	20.3	20.9	15.8	16.7	14.9
Grassland	**6.4**	**6.1**	**7.0**	**6.8**	**6.1**	**6.2**	**6.1**
Volatilization & Atm. Deposition	3.4	3.4	3.3	3.2	3.0	3.1	3.2
Surface Leaching & Run-Off	2.9	2.7	3.7	3.6	3.1	3.0	2.9
Total	**29.9**	**28.4**	**35.1**	**34.7**	**29.4**	**30.3**	**28.3**

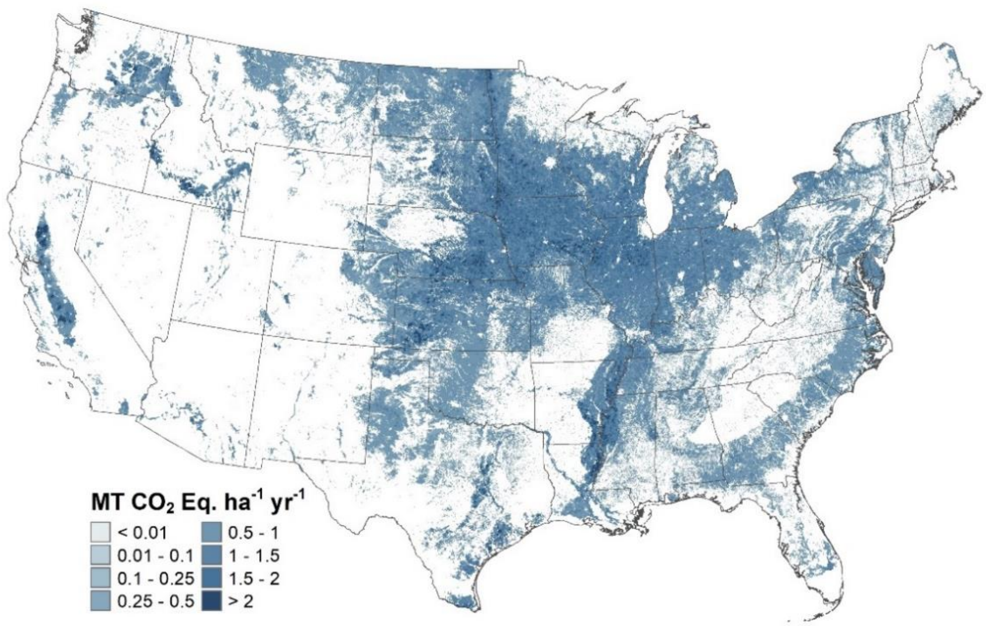
Notes: Estimates for 2021 to 2022 are based on a data splicing method, except for other organic nitrogen amendments that are based on a data splicing method for 2018 to 2022 (see Methodology section). Totals may not sum due to independent rounding.

Figure 5-5 and Figure 5-6 show regional patterns for direct N_2O emissions. Figure 5-7 and Figure 5-8 show indirect N_2O emissions from volatilization, and Figure 5-9 and Figure 5-10 show the indirect N_2O emissions from leaching and runoff in croplands and grasslands, respectively.

Direct N_2O emissions from croplands occur throughout all of the cropland regions but tend to be high in the Midwestern Corn Belt Region (particularly, Illinois, Iowa, Kansas, Minnesota, Nebraska), where a large portion of the land is used for growing highly fertilized corn and nitrogen-fixing soybean crops (see Figure 5-5). There are high emissions from the Southeastern region, and portions of the Great Plains. Emissions are also high in the Lower Mississippi River Basin from Missouri to Louisiana, and highly productive irrigated areas, such as Platte River, which flows from Colorado and Wyoming through Nebraska, Snake River Valley in Idaho, and the Central Valley in California. Direct emissions from croplands are low in mountainous regions of the Eastern United States because only a small portion of land is cultivated, and in much of the Western United States where rainfall and access to irrigation water are limited, in addition to mountainous, which are generally not suitable for crop production.

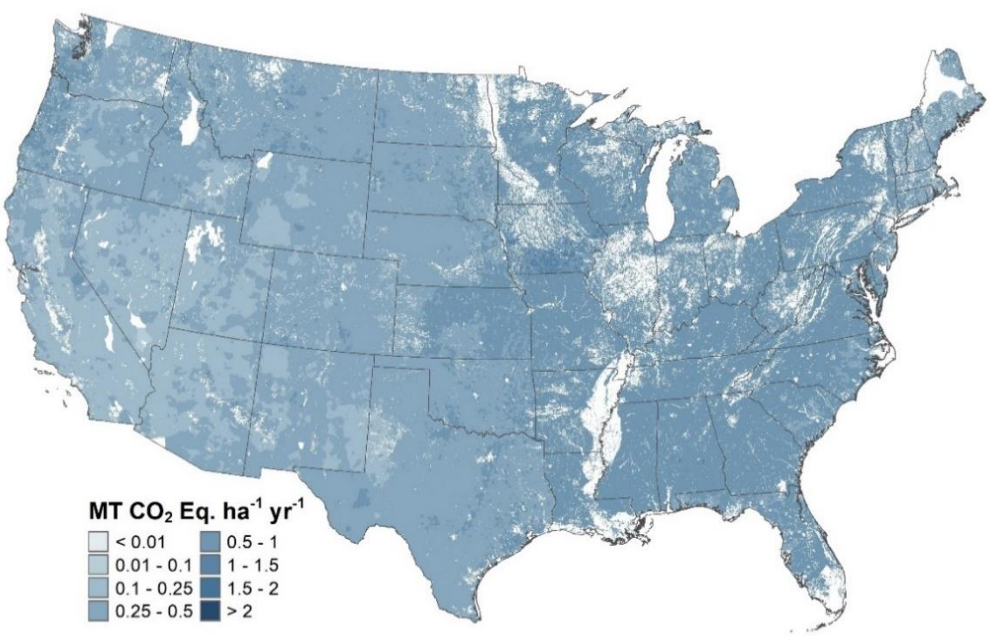
Direct N_2O emissions from grasslands are more evenly distributed throughout the United States compared to emissions from cropland due to suitable areas for grazing in most regions (see Figure 5-6). Total emissions tend be highest in the Great Plains and western United States where a large proportion of the land is dominated by grasslands with cattle and sheep grazing (particularly Kansas, Montana, Nebraska, New Mexico, Oklahoma, South Dakota, Texas).

Figure 5-5: Croplands, 2020 Annual Direct N_2O Emissions Estimated Using the Tier 3 DayCent Model



Note: Only national-scale emissions are estimated for 2022 using a splicing method, and therefore the fine-scale emission patterns in this map are based on *Inventory* data from 2020.

Figure 5-6: Grasslands, 2020 Annual Direct N_2O Emissions Estimated Using the Tier 3 DayCent Model

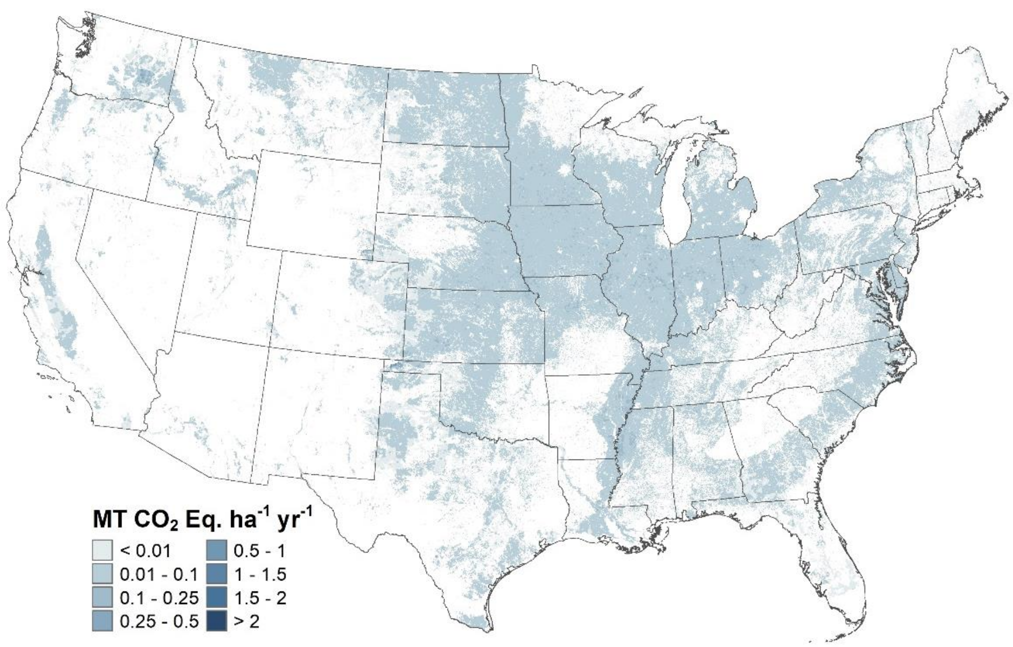


Note: Only national-scale emissions are estimated for 2022 using a splicing method, and therefore the fine-scale emission patterns in this map are based on *Inventory* data from 2020.

Indirect N_2O emissions from volatilization in croplands have a similar pattern as the direct N_2O emissions with higher emissions in the Midwestern Corn Belt, Lower Mississippi River Basin, Southeastern region, and parts of the Great Plains and irrigated areas of the Western United States. Indirect N_2O emissions from volatilization in grasslands are higher in the Eastern and Central United States, along with relatively small areas scattered around the Western United States. The higher emissions are partly due to large additions of PRP manure nitrogen, which in turn, stimulates NH_3 volatilization.

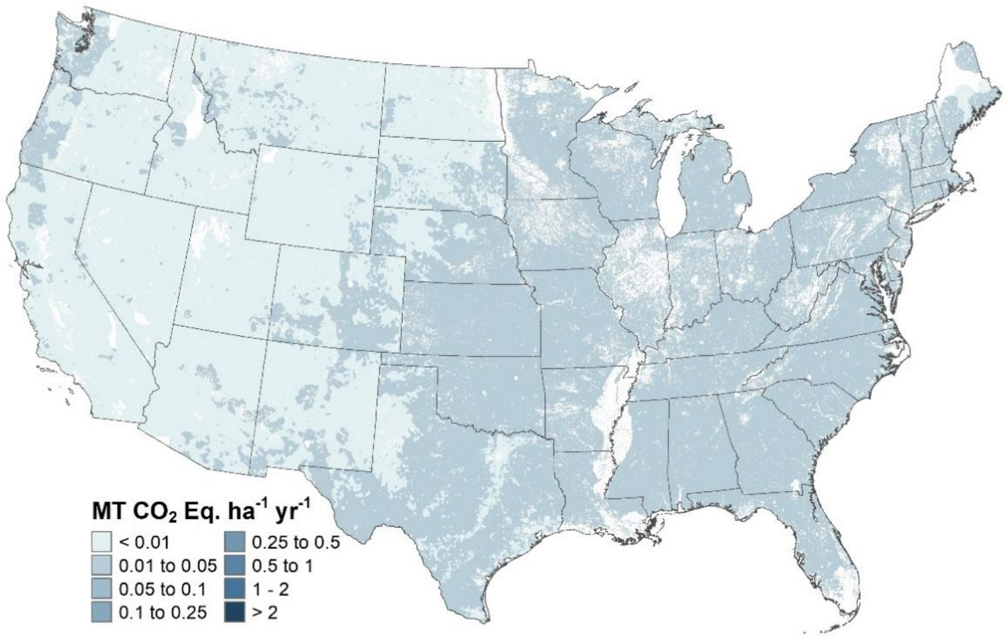
Indirect N_2O emissions from surface runoff and leaching of applied/mineralized nitrogen in croplands is highest in the Midwestern Corn Belt. There are also relatively high emissions associated with nitrogen management in the Lower Mississippi River Basin, Piedmont region of the Southeastern United States and the Mid-Atlantic states. In addition, areas of high emissions occur in portions of the Great Plains that have irrigated croplands with high leaching rates of applied/mineralized nitrogen. Indirect N_2O emissions from surface runoff and leaching of applied/mineralized nitrogen in grasslands are higher in the eastern United States and coastal Northwest region. These regions have greater precipitation and higher levels of leaching and runoff compared to arid to semi-arid regions in the Western United States.

Figure 5-7: Croplands, 2020 Annual Indirect N_2O Emissions from Volatilization Using the Tier 3 DayCent Model



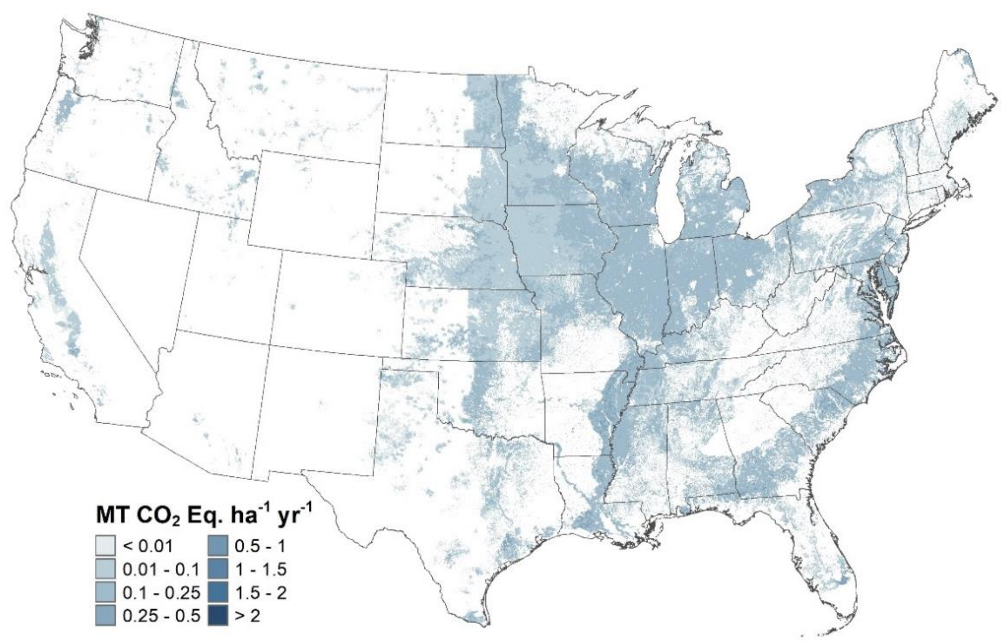
Note: Only national-scale emissions are estimated for 2022 using a splicing method, and therefore the fine-scale emission patterns in this map are based on *Inventory* data from 2020.

Figure 5-8: Grasslands, 2020 Annual Indirect N_2O Emissions from Volatilization Using the Tier 3 DayCent Model



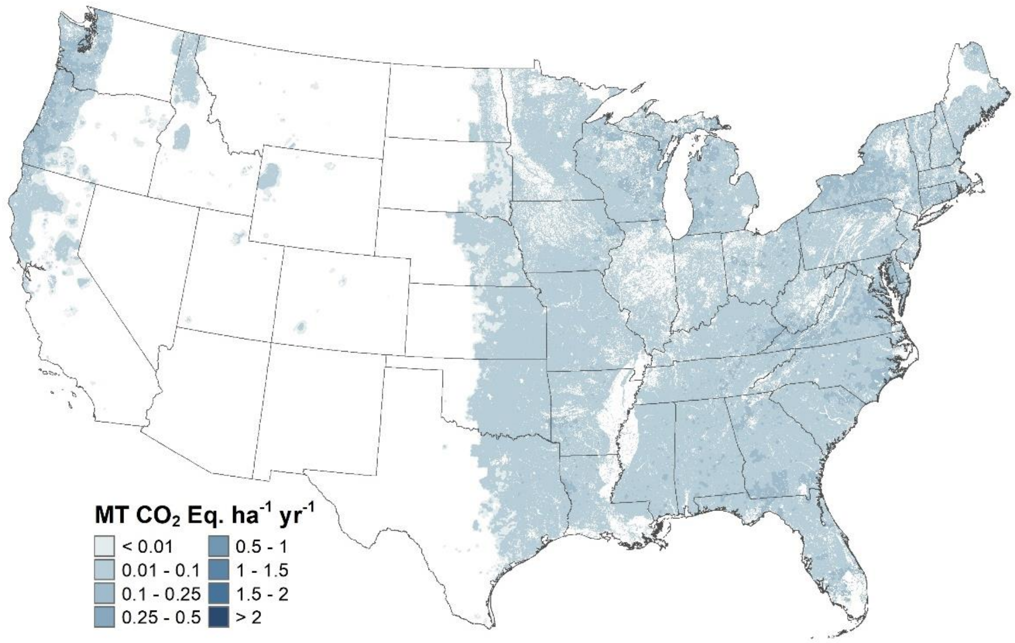
Note: Only national-scale emissions are estimated for 2022 using a splicing method, and therefore the fine-scale emission patterns in this map are based on *Inventory* data from 2020.

Figure 5-9: Croplands, 2020 Annual Indirect N_2O Emissions from Leaching and Runoff Using the Tier 3 DayCent Model



Note: Only national-scale emissions are estimated for 2022 using a splicing method, and therefore the fine-scale emission patterns in this map are based on *Inventory* data from 2020.

Figure 5-10: Grasslands, 2020 Annual Indirect N_2O Emissions from Leaching and Runoff Using the Tier 3 DayCent Model



Note: Only national-scale emissions are estimated for 2022 using a splicing method, and therefore the fine-scale emission patterns in this map are based on *Inventory* data from 2020.

Methodology and Time-Series Consistency

The *2006 IPCC Guidelines* (IPCC 2006) divide emissions from the agricultural soil management source category into five components, including (1) direct emissions from nitrogen additions to cropland and grassland mineral soils from synthetic fertilizers, biosolids (i.e., treated sewage sludge), crop residues (legume nitrogen-fixing and non-legume crops), and organic amendments; (2) direct emissions from soil organic matter mineralization due to land use and management change; (3) direct emissions from drainage of organic soils in croplands and grasslands; (4) direct emissions from soils due to manure deposited by livestock on PRP grasslands; and (5) indirect emissions from soils and water from nitrogen additions and manure deposition to soils that lead to volatilization, leaching, or runoff of nitrogen and subsequent conversion to N_2O.

In this source category, the United States reports on all croplands, as well as all managed grasslands, whereby anthropogenic greenhouse gas emissions are estimated in a manner consistent with the managed land concept (IPCC 2006), including direct and indirect N_2O emissions from asymbiotic fixation[17] and mineralization of nitrogen associated with decomposition of soil organic matter and residues. One recommendation from IPCC (2006) that has not been completely adopted is the estimation of emissions from grassland pasture renewal, which involves occasional plowing to improve forage production in pastures. Currently no data are available to address pasture renewal.

In addition, estimates of N_2O emissions from managed croplands and grasslands are not available for Alaska and Hawaii except for managed manure and PRP nitrogen, and biosolid additions for Alaska, and managed manure and

[17] Nitrogen inputs from asymbiotic nitrogen fixation are not directly addressed in *2006 IPCC Guidelines* but are a component of the nitrogen inputs and total emissions from managed lands and are included in the Tier 3 approach developed for this source.

PRP nitrogen, biosolids additions, and crop residue for Hawaii. There is a planned improvement to include the additional sources of emissions in a future *Inventory*.

Direct N_2O Emissions

The methodology used to estimate direct N_2O emissions from agricultural soil management in the United States is based on a combination of IPCC Tier 1 and 3 approaches, along with application of a splicing method for latter years in the *Inventory* time series (IPCC 2006; Del Grosso et al. 2010). A Tier 3 process-based model (DayCent) is used to estimate direct emissions from a variety of crops that are grown on mineral (i.e., non-organic) soils, as well as the direct emissions from non-federal grasslands except for applications of biosolids (i.e., treated sewage sludge) (Del Grosso et al. 2010). The Tier 3 approach has been specifically designed and tested to estimate N_2O emissions in the United States, accounting for more of the environmental and management influences on soil N_2O emissions than the IPCC Tier 1 method (see Box 5-3 for further elaboration). Moreover, the Tier 3 approach addresses direct N_2O emissions and soil carbon stock changes from mineral cropland soils in a single analysis. Carbon and nitrogen dynamics are linked in plant-soil systems through biogeochemical processes of microbial decomposition and plant production (McGill and Cole 1981). Coupling the two source categories (i.e., agricultural soil carbon and N_2O) in a single inventory analysis ensures that there is consistent activity data and treatment of the processes, and interactions are considered between carbon and nitrogen cycling in soils.

Crop and land use histories are based on the USDA National Resources Inventory (NRI) (USDA-NRCS 2020) and extended through 2020 using the USDA-NASS Crop Data Layer Product (USDA-NASS 2021; Johnson and Mueller 2010). The areas have been modified in the original NRI survey through a process in which the Forest Inventory and Analysis (FIA) survey data and the National Land Cover Dataset (Yang et al. 2018) are harmonized with the NRI data (Nelson et al. 2020). This process ensures that the land use areas are consistent across all land use categories (see Section 6.1).

The NRI is a statistically-based sample and includes 364,333 survey locations on agricultural land for the conterminous United States that are included in the Tier 3 method. The Tier 1 approach is used to estimate the emissions from an annual average of 239,757 locations in the NRI survey across the time series, which are designated as cropland or grassland (discussed later in this section). The Tier 1 method is used to estimate emissions for components that are not simulated by DayCent. DayCent has not been parametrized to simulate some crop types and soil types, as described below. Each survey location is associated with a survey weight that allows scaling of N_2O emissions from NRI survey locations to the entire country (i.e., each survey weight is an approximation of the amount of area with the same land-use/management history as the survey location). Each NRI survey location was sampled on a 5-year cycle from 1982 until 1997. For cropland, data were collected in 4 out of 5 years in the cycle (i.e., 1979 through 1982, 1984 through 1987, 1989 through 1992, and 1994 through 1997). In 1998, the NRI program began collecting annual data, which are currently available through 2017 (USDA-NRCS 2020). For 2018-2020, the time series is extended with the crop data provided in USDA-NASS CDL (USDA-NASS 2021). CDL data have a 30 to 58 m spatial resolution, depending on the year. Specifically, NRI survey locations are overlaid on the CDL in a geographic information system, and the crop types are extracted to extend the cropping histories for the inventory analysis.

Box 5-3: Tier 1 vs. Tier 3 Approach for Estimating N_2O Emissions

The IPCC (2006) Tier 1 approach is based on multiplying activity data on different nitrogen inputs (i.e., synthetic fertilizer, manure, nitrogen fixation, etc.) by the appropriate default IPCC emission factors to estimate N_2O emissions on an input-by-input basis. The Tier 1 approach requires a minimal amount of activity data, readily available in most countries (e.g., total nitrogen applied to crops); calculations are simple; and the methodology is highly transparent. In contrast, the Tier 3 approach developed for this *Inventory* is based on application of a process-based model (i.e., DayCent) that represents the interaction of nitrogen inputs, land use and management, as well as environmental conditions at specific locations, such as freeze-thaw effects that generate pulses of N_2O emissions (Wagner-Riddle et al. 2017; Del Grosso et al. 2022). Consequently, the Tier 3 approach accounts for land-use and management impacts and their interaction with environmental factors, such as weather patterns and soil characteristics, in a more comprehensive manner, which will enhance or dampen anthropogenic influences. However, the Tier 3 approach requires more detailed activity data (e.g., crop-specific nitrogen fertilization rates), additional data inputs (e.g., daily weather, soil types), and considerable computational resources and programming expertise. The Tier 3 methodology is less transparent, and thus it is critical to evaluate the output of Tier 3 methods against measured data in order to demonstrate that the method is an improvement over lower tier methods for estimating emissions (IPCC 2006). Another important difference between the Tier 1 and Tier 3 approaches relates to assumptions regarding nitrogen cycling. Tier 1 assumes that nitrogen added to a system is subject to N_2O emissions only during that year and cannot be stored in soils and contribute to N_2O emissions in subsequent years. This is a simplifying assumption that may create bias in estimated N_2O emissions for a specific year. In contrast, the process-based model in the Tier 3 approach includes the legacy effect of nitrogen added to soils in previous years that is re-mineralized from soil organic matter and emitted as N_2O during subsequent years.

DayCent is used to estimate N_2O emissions associated with production of alfalfa hay, barley, corn, cotton, dry beans, grass hay, grass-clover hay, lentils, oats, onions, peanuts, peas, potatoes, rice, sorghum, soybeans, sugar beets, sunflowers, sweet potatoes, tobacco, tomatoes, and wheat, but is not applied to estimate N_2O emissions from other crops or rotations with other crops,[18] such as sugarcane, some vegetables, and perennial/horticultural crops. Areas that are converted between agriculture (i.e., cropland and grassland) and other land uses, such as forest land, wetland and settlements, are not simulated with DayCent. DayCent is also not used to estimate emissions from land areas with very gravelly, cobbly, or shaley soils in the topsoil (greater than 35 percent by volume in the top 30 cm of the soil profile), or to estimate emissions from drained organic soils (*Histosols*). The Tier 3 method has not been fully tested for estimating N_2O emissions associated with these crops and rotations, land uses, as well as organic soils or cobbly, gravelly, and shaley mineral soils. In addition, federal grassland areas are not simulated with DayCent due to limited activity data on land use histories. For areas that are not included in the DayCent simulations, Tier 1 methods are used to estimate emissions, including (1) direct emissions from nitrogen inputs for crops on mineral soils that are not simulated by DayCent; (2) direct emissions from PRP nitrogen additions on federal grasslands; (3) direct emissions for land application of biosolids (i.e., treated sewage sludge) to soils; and (4) direct emissions from drained organic soils in croplands and grasslands.

A splicing method is used to estimate soil N_2O emissions for 2021 to 2022 at the national scale because new activity data have not been incorporated into the analysis for those years. Specifically, linear regression models with autoregressive moving-average (ARMA) errors (Brockwell and Davis 2016) are used to estimate the relationship between surrogate data and the 1990 to 2020 emissions that are derived using the Tier 3 method. Surrogate data for these regression models includes corn and soybean yields from USDA-NASS statistics,[19] and weather data from the PRISM Climate Group (PRISM 2022). For the Tier 1 method, a linear-time series model is used to estimate emissions for 2021-2022 without surrogate data. In addition, the linear time series model is used to estimate emissions data for 2018 to 2022 for other organic nitrogen amendments (i.e., commercial organic fertilizer) due to a gap in the activity data during the latter part of the time series (TVA 1991 through 1994; AAPFCO 1995 through 2022). See Box 5-4 for more information about the splicing method. Emission estimates for years with imputed data will be recalculated in future *Inventory* reports when new NRI data and other organic amendment nitrogen data are available.

[18] A small proportion of the major commodity crop production, such as corn and wheat, is included in the Tier 1 analysis because these crops are rotated with other crops or land uses (e.g., forest lands) that are not simulated by DayCent.

[19] See https://quickstats.nass.usda.gov/.

Box 5-4: Data Splicing Method

An approach to extend the time series is needed for agricultural soil management because there are typically activity data gaps at the end of the time series. This is mainly because the NRI survey program, which provides critical information for estimating greenhouse gas emissions and removals, does not release data every year.

Splicing methods have been used to impute missing data at the end of the emission time series for both the Tier 1 and 3 methods. Specifically, a linear regression model with autoregressive moving-average (ARMA) errors (Brockwell and Davis 2016) is used to estimate emissions based on the emissions data that has been compiled using the inventory methods described in this section. The model to extend the time series is given by the equation:

$$Y = X\beta + \varepsilon,$$

where Y is the response variable (e.g., soil nitrous oxide), $X\beta$ for the Tier 3 method contains specific surrogate data depending on the response variable, and ε is the remaining unexplained error. Models with a variety of surrogate data were tested, including commodity statistics, weather data, or other relevant information. The term $X\beta$ for the Tier 1 method only contains year as a predictor of emission patterns over the time series (change in emissions per year), and therefore, is a linear time series model with no surrogate data. Parameters are estimated using standard statistical techniques, and used in the model described above to predict the missing emissions data.

A critical issue with splicing methods is to account for the additional uncertainty introduced by predicting emissions without compiling the full inventory. Specifically, uncertainty will increase for years with imputed estimates based on the splicing methods, compared to those years in which the full inventory is compiled. This additional uncertainty is quantified within the model framework using a Monte Carlo approach. Consequently, the uncertainty from the original inventory data is combined with the uncertainty in the data splicing model. The approach requires estimating parameters in the data splicing models in each Monte Carlo simulation for the full inventory (i.e., the surrogate data model is refit with the draws of parameters values that are selected in each Monte Carlo iteration, and used to produce estimates with inventory data). Therefore, the data splicing method generates emissions estimates from each surrogate data model in the Monte Carlo analysis, which are used to derive confidence intervals in the estimates for the missing emissions data. Furthermore, the 95 percent confidence intervals are estimated using the 3 sigma rules assuming a unimodal density (Pukelsheim 1994).

Tier 3 Approach for Mineral Cropland Soils

The DayCent biogeochemical model (Parton et al. 1998; Del Grosso et al. 2001 and 2011) is used to estimate direct N_2O emissions from mineral cropland soils that are managed for production of a wide variety of crops (see list in previous section) based on the crop histories in the 2017 NRI (USDA-NRCS 2020) and extended through 2020 using CDL (USDA-NASS 2021). Crops simulated by DayCent are grown on approximately 85 percent of total cropland area in the United States. The model simulates net primary productivity (NPP) using the NASA-CASA production algorithm MODIS Enhanced Vegetation Index (EVI) products, MOD13Q1 and MYD13Q1[20] (Potter et al. 1993, 2007). The model simulates soil temperature and water dynamics, using daily weather data from a 4-kilometer gridded product developed by the PRISM Climate Group (2022), and soil attributes from the Soil Survey Geographic

[20] Net Primary Production is estimated with the NASA-CASA algorithm for most of the cropland that is used to produce major commodity crops in the central United States from 2000 to 2020. Other regions and years prior to 2000 are simulated with a method that incorporates water, temperature, and moisture stress on crop production (see Metherell et al. 1993) but does not incorporate the additional information about crop condition provided with remote sensing data.

Database (SSURGO) (Soil Survey Staff 2020). DayCent is used to estimate direct N_2O emissions due to mineral nitrogen available from the following sources: (1) application of synthetic fertilizers; (2) application of livestock manure; (3) retention of crop residues in the field for nitrogen-fixing legumes and non-legume crops and subsequent mineralization of nitrogen during microbial decomposition (i.e., leaving residues in the field after harvest instead of burning or collecting residues); (4) mineralization of nitrogen from decomposition of soil organic matter; and (5) asymbiotic fixation.

Management activity data from several sources supplement the activity data from the NRI. The USDA-NRCS Conservation Effects and Assessment Project (CEAP) provides data on a variety of cropland management activities, and is used to inform the inventory analysis about tillage practices, mineral fertilization, manure amendments, cover crop management, as well as planting and harvest dates (USDA-NRCS 2022; USDA-NRCS 2018; USDA-NRCS 2012). CEAP data are collected at a subset of NRI survey locations, and currently provide management information from approximately 2002 to 2006 and 2013 to 2016. These data are combined with other datasets in an imputation analysis. This imputation analysis is comprised of three steps: a) determine the trends in management activity across the time series by combining information from several datasets (discussed below); b) use Gradient Boosting (Friedman 2001) to determine the likely management practice at a given NRI survey location; and c) assign management practices from the CEAP survey to the specific NRI locations using a predictive mean matching method for certain variables that are adapted to reflect the trending information (Little 1988, van Buuren 2012). Gradient boosting is a machine learning technique used in regression and classification tasks, among others. It combines predictions from multiple weak prediction models and outperforms many complicated machine learning algorithms. It makes the best predictions at specific NRI survey locations or at state or region level models. The predictive mean matching method identifies the most similar management activity recorded in the CEAP surveys that match the prediction from the gradient boosting algorithm. The matching ensures that imputed management activities are realistic for each NRI survey location, and not odd or physically unrealizable results that could be generated by the gradient boosting. There are six complete imputations of the management activity data using these methods.

To determine trends in mineral fertilization and manure amendments, CEAP data are combined with information on fertilizer use and rates by crop type for different regions of the United States from the USDA Economic Research Service. The data collection program was known as the Cropping Practices Surveys through 1995 (USDA-ERS 1997), and is now part of data collection known as the Agricultural Resource Management Surveys (ARMS) (USDA-ERS 2020). Additional data on fertilization practices are compiled through other sources particularly the National Agricultural Statistics Service (USDA-NASS 1992, 1999, 2004). To determine the trends in tillage management, CEAP data are combined with Conservation Technology Information Center data between 1989 and 2004 (CTIC 2004) and OpTIS Data Product[21] for 2008 to 2020 (Hagen et al. 2020). The CTIC data are adjusted for long-term adoption of no-till agriculture (Towery 2001). For cover crops, CEAP data are combined with information from USDA Census of Agriculture (USDA-NASS 2012, 2017) and the OpTIS[22] data (Hagen et al. 2020). It is assumed that cover crop management was minimal prior to 1990 and the rates increased linearly over the decade to the levels of cover crop management in the CEAP survey.

The IPCC method considers crop residue nitrogen inputs and nitrogen mineralized from soil organic matter as activity data. However, they are not treated as activity data in DayCent simulations because residue production, symbiotic nitrogen fixation (e.g., legumes), mineralization of nitrogen from soil organic matter, and asymbiotic nitrogen fixation are internally generated by the model as part of the simulation. In other words, DayCent accounts for the influence of symbiotic nitrogen fixation, mineralization of nitrogen from soil organic matter and crop residue retained in the field, and asymbiotic nitrogen fixation on N_2O emissions, but these are not model inputs.

The N_2O emissions from crop residues are reduced by approximately 3 percent (the assumed average burned portion for crop residues in the United States) to avoid double counting associated with non-CO_2 greenhouse gas

[21] OpTIS data on tillage practices provided by Regrow Agriculture, Inc.

[22] OpTIS data on cover crop management provided by Regrow Agriculture, Inc.

emissions from agricultural residue burning. Estimated levels of residue burning are based on state inventory data (ILENR 1993; Oregon Department of Energy 1995; Noller 1996; Wisconsin Department of Natural Resources 1993; Cibrowski 1996).

Uncertainty in the emission estimates from DayCent is associated with input uncertainty due to missing management data in the NRI survey that is imputed from other sources; model uncertainty due to incomplete specification of carbon and nitrogen dynamics in the DayCent model parameters and algorithms; and sampling uncertainty associated with the statistical design of the NRI survey. Uncertainty is estimated with two variance components (Ogle et al. 2010). The first variance component quantifies the uncertainty in management activity data, model structure and parameterization. To assess this uncertainty, carbon and nitrogen dynamics at each NRI survey location are simulated six times using the imputation product and other model driver data. Uncertainty in parameterization and model algorithms are determined using a structural uncertainty estimator derived from fitting a linear mixed-effect model (Ogle et al. 2007; Del Grosso et al. 2010). The data is combined in a Monte Carlo stochastic simulation with 1,000 iterations for 1990 through 2020. For each iteration, there is a random selection of management data from the imputation product (select one of the six imputations), and random selection of parameter values and random effects for the linear mixed-effect model (i.e., structural uncertainty estimator). The second variance component quantifies uncertainty in scaling from the NRI survey to the entire land base. The second variance component is computed using the replicate weights provided with the NRI survey data, and a standard variance estimator for a two-stage sample design (Särndal et al. 1992). The two variance components are summed to quantify the total uncertainty and produce confidence intervals associated with the estimated emissions.

In order to ensure time-series consistency, the DayCent model is applied from 1990 to 2020, and a linear extrapolation method is used to approximate emissions for 2021 to 2022 based on the pattern in emissions data from 1990 to 2020 (see Box 5-4). The pattern is determined using a linear regression model with moving-average (ARMA) errors. Linear extrapolation is a standard data splicing method for approximating missing values at the end of an inventory time series (IPCC 2006). The time series will be updated with the Tier 3 method in the future as new activity data are incorporated into the analysis.

Nitrous oxide emissions from managed agricultural lands are the result of interactions among anthropogenic activities (e.g., nitrogen fertilization, manure application, tillage) and other driving variables, such as weather and soil characteristics. These factors influence key processes associated with nitrogen dynamics in the soil profile, including immobilization of nitrogen by soil microbial organisms, decomposition of organic matter, plant uptake, leaching, runoff, and volatilization, as well as the processes leading to N_2O production (nitrification and denitrification). It is not possible to partition N_2O emissions into each anthropogenic activity directly from model outputs due to the complexity of the interactions (e.g., N_2O emissions from synthetic fertilizer applications cannot be distinguished from those resulting from manure applications). To approximate emissions by activity, the amount of synthetic nitrogen fertilizer added to the soil, or mineral nitrogen made available through decomposition of soil organic matter and plant litter, as well as asymbiotic fixation of nitrogen from the atmosphere, is determined for each nitrogen source and then divided by the total amount of mineral nitrogen in the soil according to the DayCent model simulation. For 2021 to 2022, the contribution of each nitrogen source is based on the average of values that are estimated for 2018 to 2020. The percentages are then multiplied by the total of direct N_2O emissions in order to approximate the portion attributed to nitrogen management practices. This approach is only an approximation because it assumes that all nitrogen made available in soil has an equal probability of being released as N_2O, regardless of its source, which is unlikely to be the case (Delgado et al. 2009). However, this approach allows for further disaggregation of emissions by source of nitrogen, which is valuable for reporting purposes and is analogous to the reporting associated with the IPCC (2006) Tier 1 method, in that it associates portions of the total soil N_2O emissions with individual sources of nitrogen.

Tier 1 Approach for Mineral Cropland Soils

The IPCC (2006) Tier 1 methodology is used to estimate direct N_2O emissions for mineral cropland soils that are not simulated by DayCent (e.g., DayCent has not been parametrized to simulate all crop types and some soil types such as *Histosols*). For the Tier 1 method, estimates of direct N_2O emissions from nitrogen applications are based on mineral soil N that is made available from the following practices: (1) the application of synthetic commercial fertilizers; (2) application of managed manure and non-manure commercial organic fertilizers; and (3) decomposition and mineralization of nitrogen from above- and below-ground crop residues in agricultural fields (i.e., crop biomass that is not harvested). Non-manure commercial organic amendments are only included in the Tier 1 analysis because these data are not available at the county-level, which is necessary for the DayCent simulations. Consequently, all commercial organic fertilizer, as well as manure that is not added to crops in the DayCent simulations, are included in the Tier 1 analysis. The following sources are used to derive activity data:

- A process-of-elimination approach is used to estimate synthetic nitrogen fertilizer additions for crop areas that are not simulated by DayCent. The total amount of fertilizer used on farms has been estimated at the county-level by the USGS using sales records from 1990 to 2012 (Brakebill and Gronberg 2017). For 2013 through 2017, fertilizer sales data from AAPFCO (AAPFCO 2013 through 2022) [23] after adjusting for the proportion of on-farm application to determine the amount applied to crops. The amount of fertilizer applied after 2017 is estimated using the data splicing method described in Box 5-4 for the linear time series model. Then the portion of fertilizer applied to crops and grasslands simulated by DayCent is subtracted from the on-farm sales data (see Tier 3 Approach for mineral cropland soils and direct N_2O emissions from grassland soils sections for information on data sources), and the remainder of the total fertilizer used on farms is assumed to be applied to crops that are not simulated by DayCent. At a minimum, 3 percent of state-level on-farm fertilizer sales are assumed to be applied to cropland in the Tier 1 method.
- Similarly, a process-of-elimination approach is used to estimate manure nitrogen additions for crops that are not simulated by DayCent. The total amount of manure available for land application to soils has been estimated with methods described in the manure management section (Section 5.2) and annex (Annex 3.11). The amount of manure nitrogen applied in the Tier 3 approach to crops and grasslands is subtracted from total annual manure nitrogen available for land application (see Tier 3 Approach for mineral cropland soils and direct N_2O emissions from grassland soils sections for information on data sources). This difference is assumed to be applied to crops that are not simulated by DayCent.
- Commercial organic fertilizer additions are based on organic fertilizer consumption statistics through 2017,[24] which are converted from mass of fertilizer to units of nitrogen using average organic fertilizer nitrogen content, ranging between 2.3 to 4.2 percent across the time series (TVA 1991 through 1994; AAPFCO 1995 through 2022). Commercial fertilizers include dried manure and biosolids (i.e., treated sewage sludge), but the amounts are removed from the commercial fertilizer data to avoid double counting[25] with the manure nitrogen dataset described above and the biosolids (i.e., treated sewage sludge) amendment data discussed later in this section.
- Crop residue nitrogen is derived by combining amounts of above- and below-ground biomass, which are determined based on NRI crop area data (USDA-NRCS 2020), as extended using the CDL data (USDA-NASS 2021), crop production yield statistics (USDA-NASS 2023), dry matter fractions (IPCC 2006), linear equations to

[23] The fertilizer consumption data in AAPFCO are recorded in "fertilizer year" totals, (i.e., July to June), but are converted to calendar year totals. This is done by assuming that approximately 35 percent of fertilizer usage occurred from July to December and 65 percent from January to June (TVA 1992b).

[24] Soil N_2O emissions are imputed using data splicing methods for commercial fertilizers, i.e., other organic fertilizers, after 2017 because the activity data are not available.

[25] Commercial organic fertilizers include dried blood, tankage, compost, and other, but the dried manure and biosolids (i.e., treated sewage sludge) are also included in other datasets in this Inventory. Consequently, the proportions of dried manure and biosolids, which are provided in the reports (TVA 1991 through 1994; AAPFCO 1995 through 2022), are used to estimate the nitrogen amounts in dried manure and biosolids. To avoid double counting, the resulting nitrogen amounts for dried manure and biosolids are subtracted from the total nitrogen in commercial organic fertilizers before estimating emissions using the Tier 1 method.

estimate above-ground biomass given dry matter crop yields from harvest (IPCC 2006), ratios of below-to-above-ground biomass (IPCC 2006), and nitrogen contents of the residues (IPCC 2006). Nitrogen inputs from residue were reduced by 3 percent to account for average residue burning portions in the United States.

The total amounts of soil mineral nitrogen from applied synthetic and organic fertilizers, manure nitrogen additions and crop residues are multiplied by the IPCC (2006) default emission factor to derive an estimate of direct N_2O emissions using the Tier 1 method. Further elaboration on the methodology and data used to estimate N_2O emissions from mineral soils are described in Annex 3.12.

In order to ensure time-series consistency, the Tier 1 methods are applied from 1990 to 2020, and a linear extrapolation method[26] is used to approximate emissions for 2021 to 2022 based on the emission patterns between 1990 and 2020 (see Box 5-4). The exceptions include crop residue nitrogen which is estimating using the Tier 1 method for 1990 to 2022 with no linear extrapolation, and for other organic nitrogen fertilizers (i.e., commercial fertilizers), which are estimated with linear time series model for 2018 to 2022 due to a gap in the activity data during the latter part of the time series (TVA 1991 through 1994; AAPFCO 1995 through 2022). For the extrapolation, the emission pattern is determined using a linear regression model with moving-average (ARMA) errors. Linear extrapolation is a standard data splicing method for approximating missing values at the end of an inventory time series (IPCC 2006). As with the Tier 3 method, the time series that is based on the splicing methods will be recalculated in a future *Inventory* report with updated activity data.

Tier 1 and 3 Approaches from Mineral Grassland Soils

As with N_2O emissions from croplands, the Tier 3 process-based approach with application of the DayCent model and Tier 1 method described in IPCC (2006) are combined to estimate emissions from non-federal grasslands and PRP manure nitrogen additions for federal grasslands, respectively. Grassland includes pasture and rangeland that produce grass or mixed grass/legume forage primarily for livestock grazing. Rangelands are extensive areas of native grassland that are not intensively managed, while pastures are seeded grassland (possibly following tree removal) that may also have additional management, such as irrigation, fertilization, or inter-seeding legumes. DayCent is used to simulate N_2O emissions from NRI survey locations (USDA-NRCS 2020) on non-federal grasslands resulting from manure deposited by livestock directly onto pastures and rangelands (i.e., PRP manure), nitrogen fixation from legume seeding, managed manure amendments (i.e., manure other than PRP manure such as daily spread or manure collected from other animal waste management systems such as lagoons and digesters), and synthetic fertilizer application. Other nitrogen inputs are simulated within the DayCent framework, including nitrogen input from mineralization due to decomposition of soil organic matter and nitrogen inputs from senesced grass litter, as well as asymbiotic fixation of nitrogen from the atmosphere. The simulations used the same weather, soil, and synthetic nitrogen fertilizer data as discussed under the Tier 3 Approach in the mineral cropland soils section. Synthetic nitrogen fertilization rates are based on data from the Carbon Sequestration Rural Appraisals (CSRA) conducted by the USDA-NRCS (USDA-NRCS, unpublished data). The CSRA was a solicitation of expert knowledge from USDA-NRCS staff throughout the United States to support the *Inventory*. Biological nitrogen fixation is simulated within DayCent, and therefore is not an input to the model.

Manure nitrogen deposition from grazing animals in PRP systems (i.e., PRP manure nitrogen) is a key input of nitrogen to grasslands. The amounts of PRP manure nitrogen applied on non-federal grasslands for each NRI survey location are based on the amount of nitrogen excreted by livestock in PRP systems that is estimated in the manure management section (see Section 5.2 and Annex 3.11). The total amount of nitrogen excreted in each county is divided by the grassland area to estimate the nitrogen input rate associated with PRP manure. The resulting rates are a direct input into the DayCent simulations. The nitrogen input is subdivided between urine and dung based on a 50:50 split. DayCent simulations of non-federal grasslands accounted for approximately 71 percent of total PRP manure nitrogen in aggregate across the country.[27] The remainder of the PRP manure nitrogen in each state is assumed to be excreted on federal grasslands, and the N_2O emissions are estimated using the IPCC (2006) Tier 1 method.

Biosolids (i.e., treated sewage sludge) are assumed to be applied on grasslands.[28] Application of biosolids is estimated from data compiled by EPA (1993, 1999, 2003), McFarland (2001), and NEBRA (2007) (see Section 7.2 for a detailed discussion of the methodology for estimating treated sewage sludge available for land application application). Biosolids data are only available at the national scale, and it is not possible to associate application with specific soil conditions and weather at NRI survey locations. Therefore, DayCent could not be used to simulate the influence of biosolids on N_2O emissions from grassland soils, and consequently, emissions from biosolids are estimated using the IPCC (2006) Tier 1 method.

Soil N_2O emission estimates from DayCent are adjusted using a structural uncertainty estimator accounting for uncertainty in model algorithms and parameter values (Del Grosso et al. 2010). There is also sampling uncertainty for the NRI survey that is quantified with replicate sampling weights associated with the survey, as discussed for Tier 3 method associated with mineral cropland soils. N_2O emissions for the PRP manure nitrogen deposited on federal grasslands and applied biosolids nitrogen are estimated using the Tier 1 method by multiplying the nitrogen input by the default emission factor. Emissions from manure nitrogen are estimated at the state level and aggregated to the entire country, but emissions from biosolids nitrogen are calculated exclusively at the national scale. Further elaboration on the methodology and data used to estimate N_2O emissions from mineral soils are described in Annex 3.12.

Soil N_2O emissions and 95 percent confidence intervals are estimated for each year between 1990 and 2020 based on the Tier 1 and 3 methods, except for biosolids (discussed below). In order to ensure time-series consistency, emissions from 2021 to 2022 are estimated using a splicing method as described in Box 5-4, with a linear extrapolation based on the emission patterns in the 1990 to 2020 data. Linear extrapolation is a standard data splicing method for approximating emissions at the end of a time series (IPCC 2006). As with croplands, estimates for 2021 to 2022 will be recalculated in a future *Inventory* when the activity data are updated. Biosolids application data are compiled through 2022 in this *Inventory*, and therefore soil N_2O emissions and confidence intervals are estimated using the Tier 1 method for all years without application of the splicing method.

Tier 1 Approach for Drainage of Organic Soils in Croplands and Grasslands

The IPCC (2006) Tier 1 method is used to estimate direct N_2O emissions due to drainage of organic soils in croplands and grasslands at a state scale. State-scale estimates of the total area of drained organic soils are obtained from the 2017 NRI (USDA-NRCS 2020), and extended through 2022 using CDL (USDA-NASS 2021) and the Forest Inventory and Analysis (FIA) survey data, which is harmonized with the NRI data (Nelson et al. 2020). Organic soils are identified using soils data from the Soil Survey Geographic Database (SSURGO) (Soil Survey Staff 2020). The IPCC climate region map is used to subdivide areas into temperate and tropical climates according to the climate classification from IPCC (2006). To estimate annual emissions, the total temperate area is multiplied by the IPCC default emission factor for temperate regions, and the total tropical area is multiplied by the IPCC default emission factor for tropical regions (IPCC 2006). In order to ensure time-series consistency, the Tier 1 methods are applied from 1990 to 2022.

---

[27] A small amount of PRP nitrogen (less than 1 percent) is deposited in grazed pasture that is in rotation with annual crops and is reported in the grassland N_2O emissions.

[28] A portion of biosolids may be applied to croplands, but there is no national dataset to disaggregate the amounts between cropland and grassland.

Total Direct N_2O Emissions from Cropland and Grassland Soils

Annual direct emissions from the Tier 1 and 3 approaches for mineral and drained organic soils occurring in both croplands and grasslands are summed to obtain the total direct N_2O emissions from agricultural soil management (see Table 5-15 and Table 5-16). Further elaboration on the methodology and data used to estimate soil N_2O emissions are described in Annex 3.12.

Indirect N_2O Emissions Associated with Nitrogen Management in Cropland and Grasslands

Indirect N_2O emissions occur when synthetic nitrogen applied or made available through anthropogenic activity is transported from the soil either in gaseous or aqueous forms and later converted into N_2O. There are two pathways leading to indirect emissions. The first pathway results from volatilization of nitrogen as NO_x (nitrogen oxides) and NH_3 (ammonia) following application of synthetic fertilizer, organic amendments (e.g., manure, biosolids), and deposition of PRP manure. Nitrogen made available from mineralization of soil organic matter and residue, including nitrogen incorporated into crops and forage from symbiotic nitrogen fixation, and input of nitrogen from asymbiotic fixation also contributes to volatilized nitrogen emissions. Volatilized nitrogen can be returned to soils through atmospheric deposition, and a portion of the deposited nitrogen is emitted to the atmosphere as N_2O. The second pathway occurs via leaching and runoff of soil nitrogen (primarily in the form of NO_3^-, i.e., nitrate) that is made available through anthropogenic activity on managed lands, including organic and synthetic fertilization, organic amendments, mineralization of soil organic matter and residue, and inputs of nitrogen into the soil from asymbiotic fixation. Nitrate is subject to denitrification in water bodies, which leads to N_2O emissions. Regardless of the eventual location of the indirect N_2O emissions, the emissions are assigned to the original source of the nitrogen for reporting purposes, which here includes croplands and grasslands.

Tier 1 and 3 Approaches for Indirect N_2O Emissions from Atmospheric Deposition of Volatilized Nitrogen

The Tier 3 DayCent model and IPCC (2006) Tier 1 methods are combined to estimate the amount of nitrogen that is volatilized and eventually emitted as N_2O. DayCent is used to estimate nitrogen volatilization for land areas whose direct emissions are simulated with DayCent (i.e., most commodity and some specialty crops and most grasslands). The nitrogen inputs included are the same as described for direct N_2O emissions in the Tier 3 approach for mineral cropland and grassland soils sections. Nitrogen volatilization from all other areas is estimated using the Tier 1 method with default IPCC fractions for nitrogen subject to volatilization (i.e., synthetic and manure nitrogen on croplands not simulated by DayCent, other organic nitrogen inputs (i.e., commercial fertilizers), PRP manure nitrogen excreted on federal grasslands, and biosolids [i.e., treated sewage sludge] application on grasslands).

The IPCC (2006) default emission factor is multiplied by the amount of volatilized nitrogen generated from both DayCent and Tier 1 methods to estimate indirect N_2O emissions occurring with re-deposition of the volatilized nitrogen from 1990-2020 (see Table 5-18). A linear extrapolation data splicing method, described in Box 5-4, is applied to estimate emissions from 2021 to 2022 based on the emission patterns from 1990 to 2020. Linear extrapolation is a standard data splicing method for estimating emissions at the end of a time series (IPCC 2006). Further elaboration on the methodology and data used to estimate indirect N_2O emissions are described in Annex 3.12.

Tier 1 and 3 Approaches for Indirect N_2O Emissions from Leaching/Runoff

As with the calculations of indirect emissions from volatilized nitrogen, the Tier 3 DayCent model and IPCC (2006) Tier 1 method are combined to estimate the amount of nitrogen that is subject to leaching and surface runoff into water bodies, and eventually emitted as N_2O. DayCent is used to simulate the amount of nitrogen transported from lands in the Tier 3 Approach. Nitrogen transport from all other areas is estimated using the Tier 1 method and the IPCC (2006) default factor for the proportion of nitrogen subject to leaching and runoff associated with nitrogen applications on croplands that are not simulated by DayCent, applications of biosolids on grasslands, other organic N fertilizer applications, crop residue nitrogen inputs, and PRP manure nitrogen excreted on federal grasslands.

For both the DayCent Tier 3 and IPCC (2006) Tier 1 methods, NO_3^- leaching is assumed to be an insignificant source of indirect N_2O in cropland and grassland systems in arid regions, as discussed in IPCC (2006). In the United States, the threshold for significant NO_3^- leaching is based on the potential evapotranspiration (PET) and rainfall amount, similar to IPCC (2006), and is assumed to be negligible in regions where the amount of precipitation does not exceed 80 percent of PET (Note: All irrigated systems are assumed to have significant amounts of leaching of nitrogen even in drier climates).

For leaching and runoff data estimated by the Tier 3 and Tier 1 approaches, the IPCC (2006) default emission factor is used to estimate indirect N_2O emissions that occur in groundwater and waterways (see Table 5-18). Further elaboration on the methodology and data used to estimate indirect N_2O emissions are described in Annex 3.12.

In order to ensure time-series consistency, indirect soil N_2O emissions are estimated using the Tier 1 and 3 approaches from 1990 to 2020 and then a linear extrapolation data splicing method, described in Box 5-4, is applied to estimate emissions from 2021 to 2022 based on the emission patterns from 1990 to 2020. Linear extrapolation is a standard data splicing method for estimating emissions at the end of a time series (IPCC 2006). As with the direct N_2O emissions, the time series will be recalculated in a future *Inventory* when new activity data are incorporated into the analysis.

Uncertainty

Uncertainty is estimated for each of the following five components of N_2O emissions from agricultural soil management: (1) direct emissions simulated by DayCent; (2) the components of indirect emissions (nitrogen volatilized and leached or runoff) simulated by DayCent; (3) direct emissions estimated with the IPCC (2006) Tier 1 method; (4) the components of indirect emissions (nitrogen volatilized and leached or runoff) estimated with the IPCC (2006) Tier 1 method; and (5) indirect emissions estimated with the IPCC (2006) Tier 1 method. Uncertainty in direct emissions as well as the components of indirect emissions that are estimated from DayCent are derived from two variance components (Ogle et al. 2010). For the first component, a Monte Carlo Analysis (consistent with IPCC Approach 2) is used to address uncertainties in management activity data as well as model parameterization and structure (Del Grosso et al. 2010). The second variance component is quantifying uncertainty in scaling from the NRI survey to the entire land base, and computed using a standard variance estimator for a two-stage sample design (Särndal et al. 1992). The two variance components are combined using simple error propagation methods provided by the IPCC (2006), i.e., by taking the square root of the sum of the squares of the standard deviations of the uncertain quantities. For 2021 to 2022 (and 2018 to 2022 for other organic nitrogen fertilizers) there is additional uncertainty propagated through the Monte Carlo Analysis associated with the splicing method (See Box 5-4) except for the Tier 1 method for biosolids and crop residue nitrogen inputs, which do not use the data splicing method for 2021 to 2022.

Simple error propagation methods (IPCC 2006) are used to derive confidence intervals for direct emissions estimated with the IPCC (2006) Tier 1 method, the proportion of volatilization and leaching or runoff estimated with the IPCC (2006) Tier 1 method, and indirect N_2O emissions. Uncertainty in the splicing method is also included in the error propagation for 2021-2022 (see Box 5-4). Additional details on the uncertainty methods are provided in Annex 3.12. Table 5-19 shows the combined uncertainty for soil N_2O emissions. The estimated direct soil N_2O emissions range from 28 percent below to 28 percent above the 2022 emission estimate of 262.5 MMT CO_2 Eq. The combined uncertainty for indirect soil N_2O emissions ranges from 51 percent below to 123 percent above the 2022 estimate of 28.3 MMT CO_2 Eq.

Table 5-19: Quantitative Uncertainty Estimates of N_2O Emissions from Agricultural Soil Management in 2022 (MMT CO_2 Eq. and Percent)

Source	Gas	2022 Emission Estimate (MMT CO_2 Eq.)	Uncertainty Range Relative to Emission Estimate (MMT CO_2 Eq.)		(%)	
			Lower Bound	Upper Bound	Lower Bound	Upper Bound
Direct Soil N_2O Emissions	N_2O	262.5	189.6	335.3	-28%	+28%
Indirect Soil N_2O Emissions	N_2O	28.3	13.7	63.3	-51%	+123%

Note: Due to lack of data, uncertainties in PRP manure nitrogen production, other organic fertilizer amendments, and biosolids (i.e., treated sewage sludge) amendments to soils are currently treated as certain. These sources of uncertainty will be included in a future *Inventory* (IPCC 2006).

Additional uncertainty is associated with an incomplete estimation of N_2O emissions from managed croplands and grasslands in Hawaii and Alaska. The *Inventory* currently includes the N_2O emissions from managed manure and PRP nitrogen, and biosolid additions for Alaska and managed manure and PRP nitrogen, biosolid additions, and crop residue for Hawaii. Land areas used for agriculture in Alaska and Hawaii are small relative to major crop commodity states in the conterminous United States, so the emissions are likely to be minor for the other sources of nitrogen (e.g., synthetic fertilizer and crop residue inputs). Regardless, there is a planned improvement to include the additional sources of emissions in a future *Inventory*.

QA/QC and Verification

General (Tier 1) and category-specific (Tier 2) QA/QC activities were conducted consistent with the U.S. Inventory QA/QC plan outlined in Annex 8. DayCent results for N_2O emissions and NO_3^- leaching are compared with field data representing various cropland and grassland systems, soil types, and climate patterns (Del Grosso et al. 2005; Del Grosso et al. 2008), and further evaluated by comparing the model results to emission estimates produced using the IPCC (2006) Tier 1 method for the same sites. Nitrous oxide measurement data for cropland are available for 64 sites with 769 observations of management practice effects, and measurement data for grassland are available for 12 sites with 88 observations of management practice effects. Nitrate leaching data are available for 14 sites, representing 432 observations of management practice effects. In general, DayCent predicted N_2O emission and nitrate leaching for these sites reasonably well. See Annex 3.12 for more detailed information about the comparisons.

Databases containing input data and probability distribution functions required for DayCent simulations of croplands and grasslands and unit conversion factors have been checked. In addition, program scripts that are used to run the Monte Carlo uncertainty analysis have been checked. Errors were found in the synthetic nitrogen application rates for the Tier 3 method for a subset of years in some states, with overapplication based on comparisons to the synthetic fertilizer sales data. An error in the uncertainty calculation was found due to improper formulation of land area variances. A minor error was also identified in manure deposited in pasture, range, and paddock. Databases containing input data, emission factors, and calculations required for the Tier 1 method have been checked and updated as needed. Quality control identified a problem with error propagation in the Tier 1 uncertainty analysis associated with the emission factors. There was also an error identified in the leaching calculation based on irrigation status. All of these errors were corrected. Links between spreadsheets have also been checked, updated, and corrected as needed.

Recalculations Discussion

Several improvements have been implemented in this *Inventory* leading to recalculations, including a) updated time series of land representation data (Nelson et al. 2020), b) re-calibration of the soil carbon module in the DayCent model (See Annex 3.12); c) a more accurate output variable to estimate asymbiotic nitrogen fixation in the Tier 3 method, and d) corrections associated with manure deposited on pasture, range and paddock in addition to estimation of leaching based on irrigation status. The combined impact from these changes resulted in an average annual increase in emissions of 3.3 MMT CO_2 Eq., or 1.1 percent, from 1990 to 2021 relative to the previous *Inventory*.

Planned Improvements

Several planned improvements are underway associated with improving the DayCent biogeochemical model. These improvements include a better representation of plant phenology, particularly senescence events following grain filling in crops. In addition, crop parameters associated with temperature and water stress effects on plant production will be further improved in DayCent with additional model calibration. In addition, there is an improvement underway to calibrate the nitrogen submodule in order to more accurately predict nitrogen-gas losses and nitrate leaching rates. Experimental study sites will continue to be added for quantifying model structural uncertainty with priority given to studies that have continuous (daily) measurements of N_2O (e.g., Scheer et al. 2013). In addition, improvements are underway to simulate crop residue burning in the DayCent model based on the amount of crop residues burned according to the data that is used in the Field Burning of Agricultural Residues source category (see Section 5.7).

For Tier 1, there is a planned improvement to include all sources of nitrogen for Alaska and Hawaii in the *Inventory* for agricultural soil management, which currently only addresses managed manure nitrogen and PRP nitrogen, and biosolids additions for grasslands in both states, in addition to crop residue nitrogen inputs for Hawaii. There is also an improvement to incorporate the Tier 1 emission factor for N_2O emissions from drained organic soils by using the revised factors in the *2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands* (IPCC 2014). There is a planned improvement for the Tier 1 method associated with estimating soil N_2O emissions from nitrogen mineralization due to soil organic matter decomposition that is accelerated with land use conversions to cropland and grassland. Lastly, a review of available data on biosolids (i.e., treated sewage sludge) application will also be undertaken to improve the distribution of biosolids application on croplands, grasslands and settlements.

Improvements are expected to be completed for the next *Inventory* (i.e., 2025 submission to the UNFCCC, 1990 through 2023 *Inventory*), pending prioritization of resources.

5.5 Liming (CRT Source Category 3G)

Crushed limestone ($CaCO_3$) and dolomite ($CaMg(CO_3)_2$) are added to soils by land managers to increase soil pH (i.e., to reduce acidification). Carbon dioxide emissions occur as these compounds react with hydrogen ions in soils. The rate of degradation of applied limestone and dolomite depends on the soil conditions, soil type, climate regime, and whether limestone or dolomite is applied. Emissions from limestone and dolomite that are used in industrial processes (e.g., cement production, glass production, etc.) are reported in the IPPU chapter. Emissions from liming of soils have fluctuated between 1990 and 2022 in the United States, ranging from 2.2 MMT CO_2 Eq. to 6.0 MMT CO_2 Eq. across the entire time series. In 2022, liming of soils in the United States resulted in emissions of 3.3 MMT CO_2 Eq. (0.9 MMT C), representing a 30 percent decrease in emissions since 1990 (see Table 5-20 and Table 5-21). The trend is driven by variation in the amount of limestone and dolomite applied to soils over the time period.

Table 5-20: Emissions from Liming (MMT CO_2 Eq.)

Source	1990	2005	2018	2019	2020	2021	2022
Limestone	4.1	3.9	2.0	1.9	2.5	2.0	2.9
Dolomite	0.6	0.4	0.2	0.3	0.4	0.4	0.3
Total	**4.7**	**4.4**	**2.2**	**2.2**	**2.9**	**2.4**	**3.3**

Note: Totals may not sum due to independent rounding.

Table 5-21: Emissions from Liming (MMT C)

Source	1990	2005	2018	2019	2020	2021	2022
Limestone	1.1	1.1	0.6	0.5	0.7	0.5	0.8
Dolomite	0.2	0.1	0.1	0.1	0.1	0.1	0.1
Total	**1.3**	**1.2**	**0.6**	**0.6**	**0.8**	**0.7**	**0.9**

+ Does not exceed 0.05 MMT C.
Note: Totals may not sum due to independent rounding.

Methodology and Time-Series Consistency

Carbon dioxide emissions from application of limestone and dolomite to soils were estimated using a Tier 2 methodology consistent with IPCC (2006). The annual amounts of limestone and dolomite, which are applied to soils (see Table 5-22), were multiplied by CO_2 emission factors from West and McBride (2005). These country-specific emission factors (0.059 metric ton C/metric ton limestone, 0.064 metric ton C/metric ton dolomite) are lower than the IPCC default emission factors because they account for the portion of carbonates that are transported from soils through hydrological processes and eventually deposited in ocean basins (West and McBride 2005). This analysis of lime dissolution is based on studies in the Mississippi River basin, where the vast majority of lime application occurs in the United States (West 2008). Moreover, much of the remaining lime application is occurring under similar precipitation regimes, and so the emission factors are considered a reasonable approximation for all lime application in the United States (West 2008) (see Box 5-5).

The annual application rates of limestone and dolomite were derived from estimates and industry statistics provided in the U.S. Geological Survey (USGS) *Minerals Yearbook* (Tepordei 1994 through 2015; Willett 2007a, 2007b, 2009, 2010, 2011a, 2011b, 2013a, 2014, 2015, 2016, 2017, 2020a, 2022a, 2022b, 2022c, 2023a), as well as preliminary data that will eventually be published in the *Minerals Yearbook* for the latter part of the time series (Willett 2023b). Data for the final year of the inventory is based on the *Mineral Industry Surveys*, as discussed below (USGS 2023). The U.S. Geological Survey (USGS; U.S. Bureau of Mines prior to 1997) compiled production and use information through surveys of crushed stone manufacturers. However, manufacturers provided different levels of detail in survey responses so the estimates of total crushed limestone and dolomite production and use were divided into three components: (1) production by end-use, as reported by manufacturers (i.e., "specified" production); (2) production reported by manufacturers without end-uses specified (i.e., "unspecified" production); and (3) estimated additional production by manufacturers who did not respond to the survey (i.e., "estimated" production).

Box 5-5: Comparison of the Tier 2 U.S. Inventory Approach and IPCC (2006) Default Approach

Emissions from liming of soils were estimated using a Tier 2 methodology based on emission factors specific to the United States that are lower than the IPCC (2006) default emission factors. Most lime application in the United States occurs in the Mississippi River basin, or in areas that have similar soil and rainfall regimes as the Mississippi River basin. Under these conditions, a significant portion of dissolved agricultural lime leaches through the soil into groundwater. Groundwater moves into channels and is transported to larger rivers and eventually the ocean where $CaCO_3$ precipitates to the ocean floor (West and McBride 2005). The U.S.-specific emission factors (0.059 metric ton C/metric ton limestone and 0.064 metric ton C/metric ton dolomite) are about half of the IPCC (2006) emission factors (0.12 metric ton C/metric ton limestone and 0.13 metric ton

C/metric ton dolomite). For comparison, the 2022 U.S. emission estimate from liming of soils is 3.3 MMT CO_2 Eq. using the country-specific factors. In contrast, emissions would be estimated at 6.6 MMT CO_2 Eq. using the IPCC (2006) default emission factors.

Data on “specified” limestone and dolomite amounts were used directly in the emission calculation because the end use is provided by the manufacturers and can be used to directly determine the amount applied to soils. However, it is not possible to determine directly how much of the limestone and dolomite is applied to soils for manufacturer surveys in the “unspecified” and “estimated” categories. For these categories, the amounts of crushed limestone and dolomite applied to soils were determined by multiplying the percentage of total “specified” limestone and dolomite production that is applied to soils, by the total amounts of “unspecified” and “estimated” limestone and dolomite production. In other words, the proportion of total “unspecified” and “estimated” crushed limestone and dolomite that was applied to soils is proportional to the amount of total “specified” crushed limestone and dolomite that was applied to soils.

In addition, data were not available for 1990, 1992, and 2022 on the fractions of total crushed stone production that were limestone and dolomite, and on the fractions of limestone and dolomite production that were applied to soils. To estimate the 1990 and 1992 data, a set of average fractions were calculated using the 1991 and 1993 data. These average fractions were applied to the quantity of "total crushed stone produced or used" reported for 1990 and 1992 in the 1994 *Minerals Yearbook* (Tepordei 1996). To estimate 2022 data, 2021 fractions were applied to the 2022 estimates of total crushed stone. The basis for these estimates is from the USGS *Mineral Industry Surveys: Crushed Stone and Sand and Gravel in the First Quarter of 2023* (USGS 2023).

The primary source for limestone and dolomite activity data is the *Minerals Yearbook*, published by the Bureau of Mines through 1996 and by the USGS from 1997 to the present. In 1994, the “Crushed Stone” chapter in the *Minerals Yearbook* began rounding (to the nearest thousand metric tons) quantities for total crushed stone produced or used. It then reported revised (rounded) quantities for each of the years from 1990 to 1993. In order to minimize the inconsistencies in the activity data, these revised production numbers have been used in all of the subsequent calculations.

Table 5-22: Applied Minerals (MMT)

Mineral	1990	2005	2018	2019	2020	2021	2022
Limestone	19.0	18.1	9.4	8.9	11.6	9.3	13.5
Dolomite	2.4	1.9	0.9	1.2	1.6	1.6	1.5

The same methods are applied throughout the time series. The activity data are extended in the last two years of the time series based on proportions of specified, unspecified and estimated agricultural limestone and dolomite so that estimates are consistent with the previous year’s data. These years will be recalculated when additional data are available on the amounts of limestone and dolomite that are used for agricultural purposes.

Uncertainty

Uncertainty regarding the amount of limestone and dolomite applied to soils was estimated at ±15 percent with normal densities (Tepordei 2003; Willett 2013b). Analysis of the uncertainty associated with the emission factors included the fraction of lime dissolved by nitric acid versus the fraction that reacts with carbonic acid, and the portion of bicarbonate that leaches through the soil and is transported to the ocean. Uncertainty regarding the time associated with leaching and transport was not addressed in this analysis, but is assumed to be a relatively small contributor to the overall uncertainty (West 2005). The probability distribution functions for the fraction of lime dissolved by nitric acid and the portion of bicarbonate that leaches through the soil were represented as triangular distributions between ranges of zero and 100 percent of the estimates. The uncertainty surrounding these two components largely drives the overall uncertainty. The emission factor distributions were truncated at 0 so that emissions were not less than 0.

A Monte Carlo (Approach 2) uncertainty analysis was applied to estimate the uncertainty in CO_2 emissions from liming. The results of the Approach 2 quantitative uncertainty analysis are summarized in Table 5-23. Carbon dioxide emissions from carbonate lime application to soils in 2022 were estimated to be between 0.50 and 6.18 MMT CO_2 Eq. at the 95 percent confidence level. This confidence interval represents a range of 85 percent below to 89 percent above the 2022 emission estimate of 3.3 MMT CO_2 Eq. Some carbon in the carbonate lime applied to agricultural soils is not emitted to the atmosphere due to the dominance of the carbonate lime dissolving in carbonic acid rather than nitric acid (West and McBride 2005).

Table 5-23: Approach 2 Quantitative Uncertainty Estimates for CO_2 Emissions from Liming (MMT CO_2 Eq. and Percent)

Source	Gas	2022 Emission Estimate (MMT CO_2 Eq.)	Uncertainty Range Relative to Emission Estimate[a] (MMT CO_2 Eq.)		(%)	
			Lower Bound	Upper Bound	Lower Bound	Upper Bound
Liming	CO_2	3.3	0.50	6.18	-85%	+89%

[a] Range of emission estimates predicted by Monte Carlo stochastic simulation for a 95 percent confidence interval.

QA/QC and Verification

A source-specific QA/QC plan for liming has been developed and implemented, consistent with the U.S. Inventory QA/QC plan outlined in Annex 8. The quality control effort focused on the Tier 1 procedures for this *Inventory*, and no errors were identified in this *Inventory*.

Recalculations Discussion

Limestone and dolomite application data for 2020 and 2021 were updated with the recent published data from Willett, J.C. (2023a). With these revisions, the emissions decreased by 1 and 22 percent for 2020 and 2021 (respectively) relative to the previous *Inventory*.

Planned Improvements

At this time there are no specific planned improvements for estimating emissions from liming.

5.6 Urea Fertilization (CRT Source Category 3H)

The use of urea ($CO(NH_2)_2$) as a fertilizer leads to greenhouse gas emissions through the release of CO_2 that was fixed during the production of urea. In the presence of water and urease enzymes, urea that is applied to soils as fertilizer is converted into ammonium (NH_4^+), hydroxyl ion (OH), and bicarbonate (HCO_3^-). The bicarbonate then evolves into CO_2 and water. Emissions from urea fertilization in the United States were 5.3 MMT CO_2 Eq. (1.5 MMT C) in 2022 (Table 5-24 and Table 5-25). Carbon dioxide emissions have increased by 120 percent between 1990 and 2022 due to an increasing amount of urea that is applied to soils. The variation in emissions across the time series is driven by differences in the amounts of fertilizer applied to soils each year. Carbon dioxide emissions associated with urea used for non-agricultural purposes are reported in the IPPU chapter (Section 4.6).

Table 5-24: CO_2 Emissions from Urea Fertilization (MMT CO_2 Eq.)

Source	1990	2005	2018	2019	2020	2021	2022
Urea Fertilization	2.4	3.5	4.9	5.0	5.1	5.2	5.3

Table 5-25: CO_2 Emissions from Urea Fertilization (MMT C)

Source	1990	2005	2018	2019	2020	2021	2022
Urea Fertilization	0.7	1.0	1.3	1.4	1.4	1.4	1.5

Methodology and Time-Series Consistency

Carbon dioxide emissions from the application of urea to agricultural soils were estimated using the IPCC (2006) Tier 1 methodology following the *2006 IPCC Guidelines* Figure 11.5 decision tree for CO_2 emissions from urea fertilization.[29] The method assumes that carbon in the urea is released after application to soils and converted to CO_2. The annual amounts of urea applied to croplands (see Table 5-26) were derived from the state-level fertilizer sales data provided in *Commercial Fertilizer* reports (TVA 1991, 1992, 1993, 1994; AAPFCO 1995 through 2022).[30] These amounts were multiplied by the default IPCC (2006) emission factor (0.20 metric tons of carbon per metric ton of urea), which is equal to the carbon content of urea on an atomic weight basis. National estimates from urea fertilization also include emissions from Puerto Rico.

Fertilizer sales data are reported in fertilizer years (July previous year through June current year), so a calculation was performed to convert the data to calendar years (January through December). According to monthly fertilizer use data (TVA 1992b), 35 percent of total fertilizer used in any fertilizer year is applied between July and December of the previous calendar year, and 65 percent is applied between January and June of the current calendar year.

Fertilizer sales data for the 2018 through 2022 fertilizer years were not available for this *Inventory*. Therefore, urea application in the 2018 through 2022 fertilizer years were estimated using a linear, least squares trend of consumption over the data from the previous five years (2013 through 2017) at the state scale. A trend of five years was chosen as opposed to a longer trend as it best captures the current inter-annual variability in consumption. State-level estimates of CO_2 emissions from the application of urea to agricultural soils were summed to estimate total emissions for the entire United States. The fertilizer year data is then converted into calendar year (Table 5-26) data using the method described above.

Table 5-26: Applied Urea (MMT)

	1990	2005	2018	2019	2020	2021	2022
Urea Fertilizer[a]	3.3	4.8	6.7	6.9	7.0	7.1	7.3

[a] These numbers represent amounts applied to all agricultural land, including cropland remaining cropland, land converted to cropland, grassland remaining grassland, land converted to grassland, settlements remaining settlements, land converted to settlements, forest land remaining forest land and land converted to forest land, as it is not currently possible to apportion the data by land-use/conversion category.

The same methods were applied to the entire time series to ensure time-series consistency from 1990 through 2022. In addition, activity data are extended using a data splicing method with a linear extrapolation based on the last five years of urea fertilization data to ensure consistency in the time series. These years will be recalculated when additional data are available on urea fertilization.

[29] *2006 IPCC Guidelines* Volume 4, Chapter 11, Figure 11.5 (page 11.33)

[30] The amount of urea consumed for non-agricultural purposes in the United States is reported in the Industrial Processes and Product Use chapter, Section 4.6 Urea Consumption for Non-Agricultural Purposes.

Uncertainty

An Approach 2 Monte Carlo analysis is conducted as described by the IPCC (2006). The largest source of uncertainty is the default emission factor, which assumes that 100 percent of the carbon in $CO(NH_2)_2$ applied to soils is emitted as CO_2. The uncertainty surrounding this factor incorporates the possibility that some of the carbon may not be emitted to the atmosphere, and therefore the uncertainty range is set from 50 percent emissions to the maximum emission value of 100 percent using a triangular distribution. In addition, urea consumption data have uncertainty that is represented as a normal density. Due to the highly skewed distribution of the resulting emissions from the Monte Carlo uncertainty analysis, the estimated emissions are based on the analytical solution to the equation, and the confidence interval is approximated based on the values at 2.5 and 97.5 percentiles.

Carbon dioxide emissions from urea fertilization of agricultural soils in 2022 are estimated to be between 3.05 and 5.49 MMT CO_2 Eq. at the 95 percent confidence level. This indicates a range of 43 percent below to 3 percent above the 2022 emission estimate of 5.33 MMT CO_2 Eq. (Table 5-27).

Table 5-27: Quantitative Uncertainty Estimates for CO_2 Emissions from Urea Fertilization (MMT CO_2 Eq. and Percent)

Source	Gas	2022 Emission Estimate (MMT CO_2 Eq.)	Uncertainty Range Relative to Emission Estimate[a] (MMT CO_2 Eq.)		(%)	
			Lower Bound	Upper Bound	Lower Bound	Upper Bound
Urea Fertilization	CO_2	5.33	3.05	5.49	-43%	+3%

[a] Range of emission estimates predicted by Monte Carlo stochastic simulation for a 95 percent confidence interval.

There are additional uncertainties that are not quantified in this analysis. There is uncertainty surrounding the assumptions underlying conversion of fertilizer years to calendar years. These uncertainties are negligible over multiple years because an over- or under-estimated value in one calendar year is addressed with a corresponding increase or decrease in the value for the subsequent year. In addition, there is uncertainty regarding the fate of carbon in urea that is incorporated into solutions of urea ammonium nitrate (UAN) fertilizer. Emissions of CO_2 from UAN applications to soils are not estimated in the current *Inventory* (see Planned Improvements).

QA/QC and Verification

A source-specific QA/QC plan for Urea Fertilization has been developed and implemented, consistent with the U.S. Inventory QA/QC plan. No quality control problems were discovered in this process except a correction to the emissions factor value in documentation tables.

Recalculations Discussion

Fertilizer consumption data was updated with the latest published estimate. In turn, the fertilizer values were recalculated using the data splicing method for 2018 to 2021 based on the revised fertilizer amount for 2017. This update led to an average decrease in emissions for the years 2017 through 2021 of 0.01 MMT CO_2 Eq., or 0.1 percent. The remainder of the time series was not affected.

Planned Improvements

A key planned improvement is to incorporate Urea Ammonium Nitrate (UAN) in the estimation of Urea CO_2 emissions. Activity data for UAN have been identified, but additional information is needed to fully incorporate this type of fertilizer into the analysis, which will be completed in a future *Inventory*.

5.7 Field Burning of Agricultural Residues (CRT Source Category 3F)

Crop production creates large quantities of agricultural crop residues, which farmers manage in a variety of ways. For example, crop residues can be left in the field and possibly incorporated into the soil with tillage; collected and used as fuel, animal bedding material, supplemental animal feed, or construction material; composted and applied to soils; transported to landfills; or burned in the field. The *2006 IPCC Guidelines* does not consider field burning of crop residues to be a net source of CO_2 emissions because it is assumed the carbon released to the atmosphere as CO_2 during burning is reabsorbed during the next growing season by the crop (IPCC 2006). However, crop residue burning is a net source of CH_4, N_2O, CO, and NO_x, which are released during combustion.

In the United States, field burning of agricultural residues occurs in southeastern states, the Great Plains, and the Pacific Northwest (McCarty 2011). The primary crops that are managed with residue burning include corn, cotton, lentils, rice, soybeans, sugarcane and wheat (McCarty 2009). In 2022, CH_4 and N_2O emissions from field burning of agricultural residues were 0.6 MMT CO_2 Eq. (22 kt) and 0.2 MMT CO_2 Eq. (1 kt), respectively (Table 5-28 and Table 5-29). Annual emissions of CH_4 and N_2O have increased from 1990 to 2022 by 14 percent and 16 percent, respectively. The increase in emissions over time is partly due to higher yielding crop varieties with larger amounts of residue production and fuel loads, but also linked with an increase in the area burned for some crop types.

Table 5-28: CH_4 and N_2O Emissions from Field Burning of Agricultural Residues (MMT CO_2 Eq.)

Gas/Crop Type	1990	2005	2018	2019	2020	2021	2022
CH_4	**0.5**	**0.6**	**0.6**	**0.7**	**0.6**	**0.6**	**0.6**
Sugarcane	0.1	0.2	0.1	0.2	0.1	0.1	0.1
Wheat	0.2	0.2	0.1	0.1	0.1	0.1	0.1
Maize	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Rice	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Soybeans	+	+	+	+	+	+	+
Cotton	+	+	+	+	+	+	+
Sorghum	+	+	+	+	+	+	+
Other Small Grains	+	+	+	+	+	+	+
Peanuts	+	+	+	+	+	+	+
Legume Hay	+	+	+	+	+	+	+
Barley	+	+	+	+	+	+	+
Oats	+	+	+	+	+	+	+
Grass Hay	+	+	+	+	+	+	+
Tobacco	+	+	+	+	+	+	+
Vegetables	0.0	+	+	+	+	+	+
Peas	+	+	+	+	+	+	+
Sunflower	+	+	+	+	+	+	+
Potatoes	+	+	+	+	+	+	+
Dry Beans	+	+	+	+	+	+	+
Sugarbeets	+	+	+	+	+	+	+
Lentils	0.0	+	+	+	+	+	+
Chickpeas	0.0	0.0	0.0	0.0	0.0	0.0	0.0
N_2O	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**
Wheat	0.1	0.1	+	+	+	+	+
Maize	+	+	+	+	+	+	+
Sugarcane	+	+	+	+	+	+	+
Rice	+	+	+	+	+	+	+
Soybeans	+	+	+	+	+	+	+
Cotton	+	+	+	+	+	+	+

Peanuts	+	+	+	+	+	+	+
Other Small Grains	+	+	+	+	+	+	+
Legume Hay	+	+	+	+	+	+	+
Sorghum	+	+	+	+	+	+	+
Grass Hay	+	+	+	+	+	+	+
Barley	+	+	+	+	+	+	+
Oats	+	+	+	+	+	+	+
Potatoes	+	+	+	+	+	+	+
Peas	+	+	+	+	+	+	+
Sugarbeets	+	+	+	+	+	+	+
Tobacco	+	+	+	+	+	+	+
Sunflower	+	+	+	+	+	+	+
Vegetables	0.0	+	+	+	+	+	+
Dry Beans	+	+	+	+	+	+	+
Lentils	0.0	+	+	+	+	+	+
Chickpeas	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total	**0.7**	**0.8**	**0.8**	**0.9**	**0.8**	**0.8**	**0.8**

+ Does not exceed 0.05 MMT CO_2 Eq.
Note: Totals may not sum due to independent rounding.

Table 5-29: CH_4, N_2O, CO, and NO_x Emissions from Field Burning of Agricultural Residues (kt)

Gas/Crop Type	1990	2005	2018	2019	2020	2021	2022
CH_4	**19**	**23**	**22**	**23**	**22**	**22**	**22**
Sugarcane	4	6	5	6	5	5	5
Wheat	6	6	5	5	5	5	5
Maize	2	4	5	5	5	5	5
Rice	3	3	2	3	2	3	3
Soybeans	1	2	2	2	2	2	2
Cotton	1	2	1	1	1	1	1
Sorghum	+	+	+	+	+	+	+
Other Small Grains	+	+	+	+	+	+	+
Peanuts	+	+	+	+	+	+	+
Legume Hay	+	+	+	+	+	+	+
Barley	+	+	+	+	+	+	+
Oats	+	+	+	+	+	+	+
Grass Hay	+	+	+	+	+	+	+
Tobacco	+	+	+	+	+	+	+
Vegetables	0	+	+	+	+	+	+
Peas	+	+	+	+	+	+	+
Sunflower	+	+	+	+	+	+	+
Potatoes	+	+	+	+	+	+	+
Dry Beans	+	+	+	+	+	+	+
Sugarbeets	+	+	+	+	+	+	+
Lentils	0	+	+	+	+	+	+
Chickpeas	0	0	0	0	0	0	0
N_2O	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Wheat	+	+	+	+	+	+	+
Maize	+	+	+	+	+	+	+
Sugarcane	+	+	+	+	+	+	+
Rice	+	+	+	+	+	+	+
Soybeans	+	+	+	+	+	+	+
Cotton	+	+	+	+	+	+	+
Peanuts	+	+	+	+	+	+	+
Other Small Grains	+	+	+	+	+	+	+
Legume Hay	+	+	+	+	+	+	+
Sorghum	+	+	+	+	+	+	+

Grass Hay	+	+	+	+	+	+	+
Barley	+	+	+	+	+	+	+
Oats	+	+	+	+	+	+	+
Potatoes	+	+	+	+	+	+	+
Peas	+	+	+	+	+	+	+
Sugarbeets	+	+	+	+	+	+	+
Tobacco	+	+	+	+	+	+	+
Sunflower	+	+	+	+	+	+	+
Vegetables	0	+	+	+	+	+	+
Dry Beans	+	+	+	+	+	+	+
Lentils	0	+	+	+	+	+	+
Chickpeas	0	0	0	0	0	0	0
CO	**407**	**480**	**433**	**468**	**446**	**480**	**501**
NOx	**16**	**18**	**17**	**18**	**17**	**18**	**19**

+ Does not exceed 0.5 kt CO_2 Eq.

Note: Totals may not sum due to independent rounding.

Methodology and Time-Series Consistency

A country-specific Tier 2 method is used to estimate greenhouse gas emissions from field burning of agricultural residues from 1990 to 2014 (for more details comparing the country-specific approach to the IPCC (2006) default approach, see Box 5-6), and a data splicing method with a linear extrapolation is applied to complete the emissions time series from 2015 to 2022. The exception is sugarcane for which emissions have been estimated from 1990 to 2020, with 2021 to 2022 estimated with the data splicing method. The following equation is used to estimate the amounts of carbon and nitrogen released (R_i, where *i* is *C* or *N*) from burning.

Equation 5-1: Elemental C or N Released through Oxidation of Crop Residues

$$R_i = CP \times RCR \times DMF \times F_i \times FB \times CE$$

$$FB = \frac{AB}{CAH}$$

where,

Crop Production (CP)	=	Annual production of crop, by state, kt crop production
Residue: Crop Ratio (RCR)	=	Amount of residue produced per unit of crop production, kt residue/kt crop production
Dry Matter Fraction (DMF)	=	Amount of dry matter per unit of residue biomass for a crop, kt residue dry matter/ kt residue biomass
Fraction C or N (F_i)	=	Fraction of C or N per unit of dry matter for a crop, kt C or N /kt residue dry matter
Fraction Burned (FB)	=	Proportion of residue biomass consumed, unitless
Combustion Efficiency (CE)	=	Proportion of residue actually burned, unitless
Area Burned (AB)	=	Total area of crop burned, by state, ha
Crop Area Harvested (CAH)	=	Total area of crop harvested, by state, ha

Crop production data are available by state and year from USDA-NASS (2019) for 22 crops that are burned in the conterminous United States, including maize, rice, wheat, barley, oats, other small grains, sorghum, cotton, grass hay, legume hay, peas, sunflower, tobacco, vegetables, chickpeas, dry beans, lentils, peanuts, soybeans, potatoes, sugarbeets, and sugarcane.[31] Crop area data are based on the 2015 and 2017 National Resources Inventories (NRI) (USDA-NRCS 2018; USDA-NRCS 2020). To estimate total crop production, the crop yield data from USDA Quick Stats (USDA-NASS 2019) are multiplied by the area data for these crops from the NRI survey. The production data for the crop types are presented in Table 5-30. Alaska and Hawaii are not included in the current analysis, but there is a planned improvement to estimate residue burning emissions for these two states in a future *Inventory*.

The amount of elemental carbon or nitrogen released through oxidation of the crop residues is used in the following equation to estimate the amount of CH_4, CO, N_2O, and NO_x emissions (E_g, where g is the specific gas, i.e., CH_4, CO, N_2O, and NO_x) from the field burning of agricultural residues:

Equation 5-2: Emissions from Crop Residue Burning

$$E_g = R_i \times EF_g \times CF$$

where,

Emission ratio (EF_g) = emission ratio by gas, g CH_4-C or CO-C/g C released, or g N_2O-N or NO_x-N/g N released

Conversion Factor (CF) = conversion by molecular weight ratio of CH_4-C to C (16/12), CO-C to C (28/12), N_2O-N to N (44/28), or NO_x-N to N (30/14)

Box 5-6: Comparison of Tier 2 U.S. Inventory Approach and IPCC (2006) Default Approach

Emissions from Field Burning of Agricultural Residues are calculated using a Tier 2 methodology that is based on the method developed by the IPCC/UNEP/OECD/IEA (1997). The rationale for using the IPCC/UNEP/OECD/IEA (1997) approach rather than the method provided in the *2006 IPCC Guidelines* is as follows: (1) the equations from both guidelines rely on the same underlying variables (though the formats differ); (2) the IPCC (2006) equation was developed to be broadly applicable to all types of biomass burning, and, thus, is not specific to agricultural residues; (3) the IPCC (2006) method provides emission factors based on the dry matter content rather than emission rates related to the amount of carbon and nitrogen in the residues; and (4) the IPCC (2006) default factors are provided only for four crops (corn, rice, sugarcane, and wheat) while this *Inventory* includes emissions from twenty-one crops.

A comparison of the methods in the current Inventory and the default IPCC (2006) approach was undertaken for 2014 to determine the difference in estimates between the two approaches. To estimate greenhouse gas emissions from field burning of agricultural residues using the IPCC (2006) methodology, the following equation—cf. IPCC (2006) Equation 2.27—was used with default factors and country-specific values for mass of fuel.

Equation 5-3: Estimation of Greenhouse Gas Emissions from Fire

$$Emissions\ (kt) = AB \times M_B \times C_f \times G_{ef} \times 10^{-6}$$

where,

Area Burned (AB) = Total area of crop burned (ha)

[31] Kentucky bluegrass (produced on farms for turf grass installations) may have small areas of burning that are not captured in the sample of locations that were used in the remote sensing analysis (see Planned Improvements).

Mass of Fuel (M_B) = U.S.- Specific Values using NASS Statistics[32] (metric tons dry matter)

Combustion Factor (C_f) = IPCC (2006) default combustion factor with fuel biomass consumption (metric tons dry matter ha^{-1})

Emission Factor (G_{ef}) = IPCC (2006) emission factor (g kg^{-1} dry matter burnt)

The IPCC (2006) Tier 1 method approach resulted in 21 percent lower emissions of CH_4 and 40 percent lower emissions of N_2O compared to this *Inventory*. In summary, the IPCC/UNEP/OECD/IEA (1997) method is considered more appropriate for U.S. conditions because it is more flexible for incorporating country-specific data. Emissions are estimated based on specific carbon and nitrogen content of the fuel, which is converted into CH_4, CO, N_2O and NO_x, compared to IPCC (2006) approach that is based on dry matter rather than elemental composition.

Emissions from field burning of agricultural residues are calculated using a Tier 2 methodology that is based on the method developed by the IPCC/UNEP/OECD/IEA (1997). The rationale for using the IPCC/UNEP/OECD/IEA (1997) approach rather than the method provided in the *2006 IPCC Guidelines* is as follows: (1) the equations from both guidelines rely on the same underlying variables (though the formats differ); (2) the IPCC (2006) equation was developed to be broadly applicable to all types of biomass burning, and, thus, is not specific to agricultural residues; (3) the IPCC (2006) method provides emission factors based on the dry matter content rather than emission rates related to the amount of carbon and nitrogen in the residues; and (4) the IPCC (2006) default factors are provided only for four crops (corn, rice, sugarcane, and wheat) while this *Inventory* includes emissions from 21 crops.

A comparison of the methods in the current *Inventory* and the default IPCC (2006) approach was undertaken for 2014 to determine the difference in estimates between the two approaches. To estimate greenhouse gas emissions from field burning of agricultural residues using the IPCC (2006) methodology, the following equation—cf. IPCC (2006) Equation 2.27—was used with default factors and country-specific values for mass of fuel.

Equation 5-4: Estimation of Greenhouse Gas Emissions from Fire

$$Emissions\ (kt) = AB \times M_B \times C_f \times G_{ef} \times 10^{-6}$$

where,

Area Burned (AB) = Total area of crop burned (ha)

Mass of Fuel (M_B) = U.S.- Specific Values using NASS Statistics[33] (metric tons dry matter)

Combustion Factor (C_f) = IPCC (2006) default combustion factor with fuel biomass consumption (metric tons dry matter ha^{-1})

Emission Factor (G_{ef}) = IPCC (2006) emission factor (g kg^{-1} dry matter burnt)

The IPCC (2006) Tier 1 method approach resulted in 21 percent lower emissions of CH_4 and 40 percent lower emissions of N_2O compared to this *Inventory*. In summary, the IPCC/UNEP/OECD/IEA (1997) method is considered more appropriate for U.S. conditions because it is more flexible for incorporating country-specific data. Emissions are estimated based on specific carbon and nitrogen content of the fuel, which is converted into

[32] NASS yields are used to derive mass of fuel values because IPCC (2006) only provides default values for 4 of the 21 crops included in the *Inventory*.

[33] NASS yields are used to derive mass of fuel values because IPCC (2006) only provides default values for 4 of the 21 crops included in the *Inventory*.

CH_4, CO, N_2O and NO_x, compared to IPCC (2006) approach that is based on dry matter rather than elemental composition.

Table 5-30: Agricultural Crop Production (kt of Product)

Crop	1990	2005	2010	2018	2019	2020
Maize	296,065	371,256	398,618	NE	NE	NE
Rice	9,543	11,751	11,976	NE	NE	NE
Wheat	79,805	68,077	68,530	NE	NE	NE
Barley	9,281	5,161	3,942	NE	NE	NE
Oats	5,969	2,646	2,364	NE	NE	NE
Other Small Grains	2,651	2,051	1,803	NE	NE	NE
Sorghum	23,687	14,382	14,052	NE	NE	NE
Cotton	4,605	6,106	4,638	NE	NE	NE
Grass Hay	44,150	49,880	46,761	NE	NE	NE
Legume Hay	90,360	91,819	85,813	NE	NE	NE
Peas	51	660	839	NE	NE	NE
Sunflower	1,015	1,448	1,212	NE	NE	NE
Tobacco	1,154	337	470	NE	NE	NE
Vegetables	+	1,187	1,469	NE	NE	NE
Chickpeas	+	5	+	NE	NE	NE
Dry Beans	467	1,143	1,461	NE	NE	NE
Lentils	+	101	254	NE	NE	NE
Peanuts	1,856	2,176	1,925	NE	NE	NE
Soybeans	56,612	86,980	95,198	NE	NE	NE
Potatoes	18,924	20,026	19,279	NE	NE	NE
Sugarbeets	24,951	25,635	33,336	NE	NE	NE
Sugarcane	26,047	38,928	34,252	36,680	37,361	42,400

+ Absolute value does not exceed 0.05 MMT CO_2 Eq.
NE (Not Estimated)
Note: The amount of crop production has not been compiled for 2015 to 2021 so a data splicing method is used to estimate emissions for this portion of the time series.

The area burned is determined based on an analysis of remote sensing products (McCarty et al. 2009, 2010, 2011). The presence of fires has been analyzed at 3,600 survey locations in the NRI from 1990 to 2002 with LANDFIRE data products developed from 30 m Landsat imagery (LANDFIRE 2008), and from 2003 through 2014 using 1 km Moderate Resolution Imaging Spectroradiometer imagery (MODIS) Global Fire Location Product (MCD14ML), combining observations from Terra and Aqua satellites (Giglio et al. 2006). A sample of states are included in the analysis with high, medium and low burning rates for agricultural residues, including Arkansas, California, Florida, Indiana, Iowa and Washington. The area burned is determined directly from the analysis for these states for all crops, with the exception of sugarcane as discussed later in this section.

For other states within the conterminous United States, the area burned for the 1990 through 2014 portion of the time series is estimated from a logistical regression model that has been developed from the data collected from the remote sensing products for the six states. The logistical regression model is used to predict occurrence of fire events. Several variables are tested in the logistical regression including a) the historical level of burning in each state (high, medium or low levels of burning) based on an analysis by McCarty et al. (2011), b) year that state laws limit burning of fields, in addition to c) mean annual precipitation and mean annual temperature from a 4-kilometer gridded product from the PRISM Climate Group (2015). A K-fold model fitting procedure is used due to low frequency of burning and likelihood that outliers could influence the model fit. Specifically, the model is trained with a random selection of sample locations and evaluated with the remaining sample. This process is repeated ten times to select a model that is most common among the set of ten, and avoid models that appear to be influenced by outliers due to the random draw of survey locations for training the model. In order to address uncertainty, a Monte Carlo analysis is used to sample the parameter estimates for the logistical regression model and produce one thousand estimates of burning for each crop in the remaining forty-two states included in this *Inventory*. State-level area burned data are divided by state-level crop area data to estimate the percent of crop area burned by crop type for each state. Table 5-31 shows the resulting percentage of crop residue burned at the national scale by crop type. State-level estimates are also available upon request.

Table 5-31: U.S. Average Percent Crop Area Burned by Crop (Percent)

Crop	1990	2005	2010	2018	2019	2020
Maize	+	+	+	NE	NE	NE
Rice	12%	11%	12%	NE	NE	NE
Wheat	3%	3%	2%	NE	NE	NE
Barley	1%	1%	1%	NE	NE	NE
Oats	1%	1%	1%	NE	NE	NE
Other Small Grains	5%	4%	4%	NE	NE	NE
Sorghum	1%	1%	1%	NE	NE	NE
Cotton	7%	10%	9%	NE	NE	NE
Grass Hay	+	+	+	NE	NE	NE
Legume Hay	+	+	+	NE	NE	NE
Peas	1%	1%	1%	NE	NE	NE
Sunflower	+	+	+	NE	NE	NE
Tobacco	1%	1%	1%	NE	NE	NE
Vegetables	+	+	+	NE	NE	NE
Chickpeas	+	+	+	NE	NE	NE
Dry Beans	+	+	+	NE	NE	NE
Lentils	+	1%	1%	NE	NE	NE
Peanuts	5%	5%	5%	NE	NE	NE
Soybeans	1%	1%	1%	NE	NE	NE
Potatoes	+	+	+	NE	NE	NE
Sugarbeets	+	+	+	NE	NE	NE
Sugarcane	6%	5%	6%	4%	6%	4%

+ Does not exceed 0.5 percent.
NE (Not Estimated)

The method for estimating burned area of sugarcane is similar to the approach for other crops. Areas with sugarcane production are identified in the 2017 USDA NRI survey (USDA-NRCS 2020) based on Cropland Data Layer (USDA-NASS 2021).[34] We use the MODIS burned area product from 2002 to 2020 to identify NRI survey locations with sugarcane production that have residue burning, similar to the process for other crops described above (Giglio et al. 2015). However, area of residue burning for sugarcane was estimated for 1990 to 2001 using a linear extrapolation of the area burned from 2002 to 2020, instead of analyzing the remote sensing data for this portion of the time series. This approach is a common data splicing method for filling data gaps in time series (IPCC 2006).

Additional parameters are needed to estimate emissions from the area that has residue burning, including residue: crop ratios, dry matter fractions, carbon fractions, nitrogen fractions and combustion efficiency. Residue: crop product mass ratios, residue dry matter fractions, and the residue N contents are obtained from several sources (IPCC 2006 and sources at bottom of Table 5-32). The residue carbon contents for all crops are based on IPCC (2006) default value for herbaceous biomass. The combustion efficiency is assumed to be 90 percent for all crop types (IPCC/UNEP/OECD/IEA 1997). See Table 5-32 for a summary of the crop-specific conversion factors. Emission ratios and mole ratio conversion factors for all gases are based on the *Revised 1996 IPCC Guidelines* (IPCC/UNEP/OECD/IEA 1997) (see Table 5-33).

[34] USDA-NRI program aggregates sugarcane with other crops, but areas planted with sugarcane are identified in the USDA-NASS Crop Data Layer.

Table 5-32: Parameters for Estimating Emissions from Field Burning of Agricultural Residues

Crop	Residue/Crop Ratio	Dry Matter Fraction	Carbon Fraction	Nitrogen Fraction	Combustion Efficiency (Fraction)
Maize	0.707	0.56	0.47	0.01	0.90
Rice	1.340	0.89	0.47	0.01	0.90
Wheat	1.725	0.89	0.47	0.01	0.90
Barley	1.181	0.89	0.47	0.01	0.90
Oats	1.374	0.89	0.47	0.01	0.90
Other Small Grains	1.777	0.88	0.47	0.01	0.90
Sorghum	0.780	0.60	0.47	0.01	0.90
Cotton	7.443	0.93	0.47	0.01	0.90
Grass Hay	0.208	0.90	0.47	0.02	0.90
Legume Hay	0.290	0.67	0.47	0.01	0.90
Peas	1.677	0.91	0.47	0.01	0.90
Sunflower	1.765	0.88	0.47	0.01	0.90
Tobacco	0.300	0.87	0.47	0.01	0.90
Vegetables	0.708	0.08	0.47	0.01	0.90
Chickpeas	1.588	0.91	0.47	0.01	0.90
Dry Beans	0.771	0.90	0.47	0.01	0.90
Lentils	1.837	0.91	0.47	0.02	0.90
Peanuts	1.600	0.94	0.47	0.02	0.90
Soybeans	1.500	0.91	0.47	0.01	0.90
Potatoes	0.379	0.25	0.47	0.02	0.90
Sugarbeets	0.196	0.22	0.47	0.02	0.90
Sugarcane	0.410	0.25	0.47	0.02	0.90

NE (Not Estimated)

Notes: Chickpeas: IPCC (2006), Table 11.2; values are for Beans & pulses.

Cotton: Combined sources (Heitholt et al. 1992; Halevy 1976; Wells and Meredith 1984; Sadras and Wilson 1997; Pettigrew and Meredith 1997; Torbert and Reeves 1994; Gerik et al. 1996; Brouder and Cassmen 1990; Fritschi et al. 2003; Pettigrew et al. 2005; Bouquet and Breitenbeck 2000; Mahroni and Aharonov 1964; Bange and Milroy 2004; Hollifield et al. 2000; Mondino et al. 2004; Wallach et al. 1978).

Lentils: IPCC (2006), Table 11.2; Beans & pulses.

Peas: IPCC (2006), Table 11.2; values are for Beans & pulses.

Peanuts: IPCC (2006); Table 11.2; Root ratio and belowground N content values are for Root crops, other.

Sugarbeets: IPCC (2006); Table 11.2; values are for Tubers.

Sunflower: IPCC (2006), Table 11.2; values are for Grains.

Sugarcane: combined sources (Wiedenfels 2000, Dua and Sharma 1976; Singels & Bezuidenhout 2002; Stirling et al. 1999; Sitompul et al. 2000).

Tobacco: combined sources (Beyaert 1996; Moustakas and Ntzanis 2005; Crafts-Brandner et al. 1994; Hopkinson 1967; Crafts-Brandner et al. 1987).

Vegetables (Combination of carrots, lettuce/cabbage, melons, onions, peppers and tomatoes):

Carrots: McPharlin et al. (1992); Gibberd et al. (2003); Reid and English (2000); Peach et al. (2000); see IPCC Tubers for R:S and N fraction.

Lettuce, cabbage: combined sources (Huett and Dettman 1991; De Pinheiro Henriques & Marcelis 2000; Huett and Dettman 1989; Peach et al. 2000; Kage et al. 2003; Tan et al. 1999; Kumar et al. 1994; MacLeod et al. 1971; Jacobs et al. 2004; Jacobs et al. 2001; Jacobs et al. 2002); values from IPCC Grains used for N fraction.

Melons: Valantin et al. (1999); squash for R:S; IPCC Grains for N fraction.

Onion: Peach et al. (2000), Halvorson et al. (2002); IPCC (2006) Tubers for N fraction.

Peppers: combined sources (Costa and Gianquinto 2002; Marcussi et al. 2004; Tadesse et al. 1999; Diaz-Perez et al. 2008); IPCC Grains for N fraction.

Tomatoes: Scholberg et al. (2000a,b); Akintoye et al. (2005); values for AGR-N and BGR-N are from Grains.

Table 5-33: Greenhouse Gas Emission Ratios and Conversion Factors

Gas	Emission Ratio	Conversion Factor
CH_4:C	0.005[a]	16/12
CO:C	0.060[a]	28/12
N_2O:N	0.007[b]	44/28
NO_x:N	0.121[b]	30/14

[a] Mass of C compound released (units of C) relative to mass of total C released from burning (units of C).
[b] Mass of N compound released (units of N) relative to mass of total N released from burning (units of N).

To ensure time-series consistency, the same method is applied from 1990 to 2014 for all crops except sugarcane in which the method was applied for 1990 to 2020. For this *Inventory*, new activity data on the burned areas have not been analyzed for 2015 to 2022 for individual crops. The exception is sugarcane in which burned areas have not been analyzed for 2021 to 2022. To complete the emissions time series, a linear extrapolation of the trend is applied to estimate the emissions for the latter part of the time series. Specifically, a linear regression model with autoregressive moving-average (ARMA) errors is used to estimate the trend in emissions over time from 1990 through 2014, and the trend is used to approximate the CH_4, N_2O, CO and NO_x from 2015 to 2022 for all crops except for sugarcane, which was estimated using this method for 2021 to 2022 (Brockwell and Davis 2016). This extrapolation method is consistent with data splicing methods in IPCC (2006). The Tier 2 method described previously will be applied to recalculate the emissions for the latter part of the time series in a future *Inventory*.

Uncertainty

Emissions are estimated using a linear regression model with autoregressive moving-average (ARMA) errors for 2022. The linear regression ARMA model produced estimates of the upper and lower bounds to quantify uncertainty, and the results are summarized in Table 5-34. Methane emissions from field burning of agricultural residues in 2022 are between 0.55 and 0.70 MMT CO_2 Eq. at a 95 percent confidence level. This indicates a range of 11 percent below and 11 percent above the 2022 emission estimate of 0.6 MMT CO_2 Eq. Nitrous oxide emissions are between 0.18 and 0.23 MMT CO_2 Eq., or approximately 13 percent below and 13 percent above the 2022 emission estimate of 0.2 MMT CO_2 Eq.

Table 5-34: Approach 2 Quantitative Uncertainty Estimates for CH_4 and N_2O Emissions from Field Burning of Agricultural Residues (MMT CO_2 Eq. and Percent)

Source	Gas	2022 Emission Estimate (MMT CO_2 Eq.)	Uncertainty Range Relative to Emission Estimate[a] (MMT CO_2 Eq.)		(%)	
			Lower Bound	Upper Bound	Lower Bound	Upper Bound
Field Burning of Agricultural Residues	CH_4	0.6	0.55	0.70	-11%	+11%
Field Burning of Agricultural Residues	N_2O	0.2	0.18	0.23	-13%	+13%

[a] Range of emission estimates predicted by Monte Carlo stochastic simulation for a 95 percent confidence interval.

Due to data limitations, there are additional uncertainties in agricultural residue burning, particularly the potential omission of burning associated with Kentucky bluegrass (produced on farms for turf grass installation).

QA/QC and Verification

A source-specific QA/QC plan for field burning of agricultural residues is implemented with Tier 1 analyses, consistent with the U.S. Inventory QA/QC plan outlined in Annex 8. Quality control measures included checking input data, model scripts, and results to ensure data are properly handled throughout the inventory process.

Inventory reporting forms and text are reviewed and revised as needed to correct transcription errors. An error was identified in the calculation of the emissions using the IPCC (2006) equation after the initial compilation, which was corrected in Box 5.6. An error was also found with the estimation of non-CO_2 emissions from burning of sugarcane residue related to the GWP factors. This error was corrected.

Recalculations Discussion

Recalculations have been conducted for this *Inventory* associated with the addition of residue burning from sugarcane, which was not included in the previous *Inventory*. As a result of this change, CH_4 emissions increased by an annual average of 0.14 MMT CO_2 Eq., or 32 percent, over the time series from 1990 to 2021 compared to the previous *Inventory*. In addition, N_2O emissions increased by an annual average of 0.03 MMT CO_2 Eq., or 21 percent, over the time series from 1990 to 2021 compared to the previous *Inventory*.

Planned Improvements

A key planned improvement is to estimate the emissions associated with field burning of agricultural residues in the states of Alaska and Hawaii. In addition, a method is in development that will directly link agricultural residue burning with the Tier 3 methods that are used in several other source categories, including agricultural soil management, cropland remaining cropland, and land converted to cropland chapters of the *Inventory*. The method is based on simulating burning events directly within the DayCent process-based model framework using information derived from remote sensing fire products as described in the Methodology section. This improvement will lead to greater consistency in the methods across sources, ensuring mass balance of carbon and nitrogen in the *Inventory* analysis.