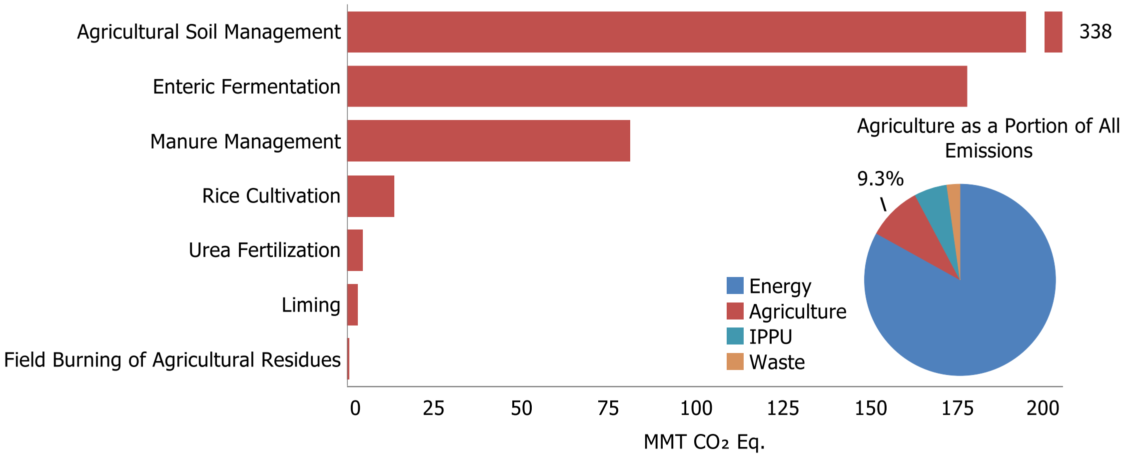
5. Agriculture

Agricultural activities contribute directly to emissions of greenhouse gases through a variety of processes. This chapter provides an assessment of methane (CH_4) and nitrous oxide (N_2O) emissions from enteric fermentation in domestic livestock, livestock manure management, rice cultivation, agricultural soil 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, grassland fires and conversion of forest land to cropland, are presented in the Land Use, Land-Use Change, and Forestry (LULUCF) chapter. Carbon dioxide emissions from on-farm energy use are reported in the Energy chapter.

Figure 5-1: 2018 Agriculture Chapter Greenhouse Gas Emission Sources (MMT CO_2 Eq.)



In 2018, the Agriculture sector was responsible for emissions of 618.5 MMT CO_2 Eq.,[1] or 9.3 percent of total U.S. greenhouse gas emissions.[2] Methane emissions from enteric fermentation and manure management represent 28.0 percent and 9.7 percent of total CH_4 emissions from anthropogenic activities, 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. Emissions of N_2O by agricultural soil management through activities such as fertilizer application and other agricultural practices that increased nitrogen availability in the soil was the largest source of U.S. N_2O emissions, accounting for 77.8 percent. Manure management and field burning

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[1] Following the current reporting requirements under the United Nations Framework Convention on Climate Change (UNFCCC), this Inventory report presents CO_2 equivalent values based on the *IPCC Fourth Assessment Report* (AR4) GWP values. See the Introduction chapter for more information.

[2] Emissions reported in the Agriculture chapter include those from all states, including Hawaii and Alaska; however, U.S. Territories are not included.

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 2018, CO_2 and CH_4 emissions from agricultural activities increased by 16.0 percent and 16.2 percent, respectively, while N_2O emissions from agricultural activities fluctuated from year to year, but increased by 8.4 percent overall.

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

Gas/Source	1990	2005	2014	2015	2016	2017	2018
CO_2	**6.7**	**7.5**	**7.5**	**7.8**	**7.1**	**7.6**	**7.7**
Urea Fertilization	2.0	3.1	3.9	4.1	4.0	4.5	4.6
Liming	4.7	4.3	3.6	3.7	3.1	3.1	3.1
CH_4	**217.6**	**238.8**	**234.3**	**241.0**	**245.3**	**248.4**	**253.0**
Enteric Fermentation	164.2	168.9	164.2	166.5	171.8	175.4	177.6
Manure Management	37.1	51.6	54.3	57.9	59.6	59.9	61.7
Rice Cultivation	16.0	18.0	15.4	16.2	13.5	12.8	13.3
Field Burning of Agricultural Residues	0.3	0.4	0.4	0.4	0.4	0.4	0.4
N_2O	**330.1**	**329.6**	**366.7**	**365.8**	**348.1**	**346.2**	**357.8**
Agricultural Soil Management	315.9	313.0	349.2	348.1	329.8	327.4	338.2
Manure Management	14.0	16.4	17.3	17.5	18.1	18.7	19.4
Field Burning of Agricultural Residues	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Total	**554.4**	**575.9**	**608.6**	**614.6**	**600.5**	**602.3**	**618.5**

Note: Totals may not sum due to independent rounding.

Table 5-2: Emissions from Agriculture (kt)

Gas/Source	1990	2005	2014	2015	2016	2017	2018
CO_2	**6,678**	**7,499**	**7,532**	**7,819**	**7,122**	**7,594**	**7,745**
Urea Fertilization	2,011	3,150	3,923	4,082	4,041	4,514	4,598
Liming	4,667	4,349	3,609	3,737	3,081	3,080	3,147
CH_4	**8,705**	**9,553**	**9,371**	**9,639**	**9,813**	**9,938**	**10,119**
Enteric Fermentation	6,566	6,755	6,567	6,660	6,874	7,016	7,103
Manure Management	1,485	2,062	2,172	2,316	2,385	2,395	2,467
Rice Cultivation	640	720	616	648	539	510	533
Field Burning of Agricultural Residues	14	16	16	16	16	16	16
N_2O	**1,108**	**1,106**	**1,231**	**1,227**	**1,168**	**1,162**	**1,201**
Agricultural Soil Management	1,060	1,050	1,172	1,168	1,107	1,099	1,135
Manure Management	47	55	58	59	61	63	65
Field Burning of Agricultural Residues	1	1	1	1	1	1	1

Note: Totals may not sum due to independent rounding.

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

In following the United Nations Framework Convention on Climate Change (UNFCCC) requirement under Article 4.1 to develop and submit national greenhouse gas emission inventories, 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 manner in line with the UNFCCC reporting guidelines for the reporting of inventories under this international agreement. The use of consistent methods to calculate emissions and removals by all nations providing their inventories to the UNFCCC ensures that these reports are comparable. The presentation of Agriculture chapter emissions and removals provided in this Inventory do not preclude alternative examinations, but rather, this Inventory presents emissions and removals in a common format consistent with how countries are to report Inventories under the UNFCCC. The report itself, and this chapter, follows this standardized format, and provides an explanation of the application of methods used to calculate emissions and removals from agricultural activities.

5.1 Enteric Fermentation (CRF 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.

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 2018 were 177.6 MMT CO_2 Eq. (7,103 kt). Beef cattle remain the largest contributor of CH_4 emissions from enteric fermentation, accounting for 72 percent in 2018. Emissions from dairy cattle in 2018 accounted for 25 percent, and the remaining emissions were from horses, sheep, swine, goats, American bison, mules and asses.[3]

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

Livestock Type	1990	2005	2014	2015	2016	2017	2018
Beef Cattle	119.1	125.2	116.5	118.0	123.0	126.3	128.1
Dairy Cattle	39.4	37.6	42.0	42.6	43.0	43.3	43.6
Swine	2.0	2.3	2.4	2.6	2.6	2.7	2.8
Horses	1.0	1.7	1.5	1.4	1.4	1.3	1.2
Sheep	2.3	1.2	1.0	1.1	1.1	1.1	1.1
American Bison	0.1	0.4	0.4	0.4	0.4	0.4	0.4
Goats	0.3	0.4	0.3	0.3	0.3	0.3	0.3
Mules and Asses	+	0.1	0.1	0.1	0.1	0.1	0.1

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[3] Enteric fermentation emissions from camels and poultry are not estimated for this Inventory. See Annex 5 for more information on sources and sinks of greenhouse gas emissions not included in this Inventory.

Total	164.2		168.9		164.2	166.5	171.8	175.4	177.6

+ 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)

Livestock Type	1990		2005		2014	2015	2016	2017	2018
Beef Cattle	4,763		5,007		4,660	4,722	4,919	5,052	5,125
Dairy Cattle	1,574		1,503		1,679	1,706	1,722	1,730	1,744
Swine	81		92		96	102	105	108	111
Horses	40		70		60	57	54	51	48
Sheep	91		49		42	42	42	42	42
American Bison	4		17		14	14	15	15	15
Goats	13		14		13	13	13	13	14
Mules and Asses	1		2		3	3	3	3	3
Total	**6,566**		**6,755**		**6,567**	**6,660**	**6,874**	**7,016**	**7,103**

Note: Totals may not sum due to independent rounding.

From 1990 to 2018, emissions from enteric fermentation have increased by 8.2 percent. Emissions have also increased from 2017 to 2018 by 1.2 percent, largely driven by an increase in beef cattle populations. While emissions generally follow trends in cattle populations, over the long term there are exceptions. For example, while dairy cattle emissions increased 4.6 percent over the entire time series, the population has declined by 2.6 percent, and milk production increased 57 percent (USDA 2019). 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 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 U.S.). Dairy cattle emissions have continued to trend upward since 2007, in line with dairy cattle population increases. Regarding trends in other animals, populations of sheep have steadily declined, with an overall decrease of 54 percent since 1990. Horse populations are 22 percent greater than they were in 1990, but their numbers have been declining by an average of 4 percent annually since 2007. Goat populations increased by about 20 percent through 2007, steadily decreased through 2012, then increased again, by about 1 percent annually, through 2018, Swine populations have trended upward through most of the time series, increasing 37 percent from 1990 to 2018. The population of American bison more than tripled over the 1990 to 2018 time period, while the population of mules and asses increased by a factor of 5.

Methodology

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*.

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, incorporates this information and other analyses of livestock population, feeding practices, and production characteristics. For the current Inventory, CEFM results for 1990 through 2017 were carried over from the 1990 to 2017 Inventory (i.e., 2019 Inventory submission), and a simplified approach was used to estimate 2018 enteric emissions from cattle.

1990 to 2017 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 2016).

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.

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

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. More details are provided in Annex 3.10.

2018 Inventory Methodology for Cattle

As noted above, a simplified approach for cattle enteric emissions was used in lieu of the CEFM for 2018. First, 2018 populations for each of the CEFM cattle sub-populations were estimated, then these populations were multiplied by the corresponding implied emission factors developed from the CEFM for the previous Inventory year. Dairy cow, beef cow, and bull populations for 2018 were based on data directly from the USDA-NASS *QuickStats* database (USDA 2019). Because the remaining CEFM cattle sub-population categories do not correspond exactly to the remaining *QuickStats* cattle categories, 2018 populations for these categories were estimated by extrapolating the 2017 populations based on percent changes from 2017 to 2018 in similar *QuickStats* categories, consistent with Volume 1, Chapter 5 of the *2006 IPCC Guidelines* on time-series consistency. Table 5-5 lists the *QuickStats* categories used to estimate the percent change in population for each of the CEFM categories.

Table 5-5: Cattle Sub-Population Categories for 2018 Population Estimates

CEFM Cattle Category	USDA-NASS *Quickstats* Cattle Category
Dairy Calves	Cattle, Calves
Dairy Cows	Cattle, Cows, Milk
Dairy Replacements 7-11 months	Cattle, Heifers, GE 500 lbs, Milk Replacement
Dairy Replacements 12-23 months	Cattle, Heifers, GE 500 lbs, Milk Replacement
Bulls	Cattle, Bulls, GE 500 lbs
Beef Calves	Cattle, Calves
Beef Cows	Cattle, Cows, Beef
Beef Replacements 7-11 months	Cattle, Heifers, GE 500 lbs, Beef Replacement

Beef Replacements 12-23 months	Cattle, Heifers, GE 500 lbs, Beef Replacement
Steer Stockers	Cattle, Steers, GE 500 lbs
Heifer Stockers	Cattle, Heifers, GE 500 lbs, (Excl. Replacement)
Steer Feedlot	Cattle, On Feed
Heifer Feedlot	Cattle, On Feed

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. Methane emissions from these animals accounted for a minor portion of total CH_4 emissions from livestock in the United States from 1990 through 2018. 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 2018 for sheep; swine; goats; horses; mules and asses; and American bison were obtained for available years from USDA-NASS (USDA 2016). Horse, goat and mule and ass population data were available for 1987, 1992, 1997, 2002, 2007, and 2012 (USDA 1992, 1997, 2016); the remaining years between 1990 and 2018 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, and 2012 (USDA 2016) 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). 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).

See Annex 3.10 for more detailed information on the methodology and data used to calculate CH_4 emissions from enteric fermentation.

Uncertainty and Time-Series Consistency

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 2018 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.

The uncertainty ranges associated with the activity data-related input variables were plus or minus 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 5-6. Based on this analysis, enteric fermentation CH_4 emissions in 2018 were estimated to be between 158.1 and 209.6 MMT CO_2 Eq. at a 95 percent confidence level, which indicates a range of 11 percent below to 18 percent above the 2018 emission estimate of 177.6 MMT CO_2 Eq. 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 previous uncertainty analysis because the Food and Agricultural Organization of the United Nations (FAO) 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 now from the same USDA source as the other animal types, 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.

Table 5-6: Approach 2 Quantitative Uncertainty Estimates for CH_4 Emissions from Enteric Fermentation (MMT CO_2 Eq. and Percent)

Source	Gas	2018 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	177.6	158.1	209.6	-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 2018 estimates.

[c] The overall uncertainty calculated in 2003, and applied to the 2018 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.

Details on the emission trends through time are described in more detail in the Methodology section.

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.

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 now utilizes the 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 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

No recalculations were performed for the 1990 to 2017 estimates. The 2018 estimates were developed using a simplified approach, as noted earlier in the chapter.

Planned Improvements

Regular annual data reviews and updates are necessary to maintain an emissions inventory that reflects the current base of knowledge. EPA conducts the following list of regular annual assessments of data availability 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;
- Updating the diet data to incorporate monthly or annual milk fat data in place of the fixed IPCC default value of 4 percent milk fat. Recent improvements efforts have yielded information that the 4 percent value is still representative of U.S. milk fat for the year 2018, but EPA continues to investigate the availability of data across the time series;
- 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;
- 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;
- 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 have implications for regular updates once addressed:

- Potentially updating to a Tier 2 methodology for other animal types (i.e., sheep, swine, goats, horses);
- Investigation of methodologies and emission factors for including enteric fermentation emission estimates from poultry;
- Comparison of the current CEFM processing of animal population data to estimates developed using annual average populations to determine if the model could be simplified to use annual population data;
- 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;
- 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; and
- Analysis and integration of a more representative spatial distribution of animal populations by state, particularly for poultry animal populations.

EPA received comments during the Public Review period of the 1990 to 2017 Inventory regarding the CEFM model and data and assumptions used to calculate enteric fermentation cattle emissions. Many of the comments received are consistent with potential planned improvement options listed above. EPA is investigating these 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.

In addition to the potential improvements listed above, EPA will review the final 2019 Refinement to the *2006 IPCC Guidelines* and incorporate any changes, as applicable, to update the current Inventory estimation data and methodologies.

5.2 Manure Management (CRF Source Category 3B)

The treatment, storage, and transportation of livestock manure can produce anthropogenic CH_4 and N_2O emissions. 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 or poultry manure are 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 and urine.[5] 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

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[5] 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.

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. 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 2018 were 61.7 MMT CO_2 Eq. (2,467 kt); in 1990, emissions were 37.1 MMT CO_2 Eq. (1,485 kt). This represents a 66 percent increase in emissions from 1990. Emissions increased on average by 1.0 MMT CO_2 Eq. (2.0 percent) annually over this period. The majority of this increase is due to swine and dairy cow manure, where emissions increased 43 and 119 percent, respectively. From 2017 to 2018, there was a 3.0 percent increase in total CH_4 emissions from manure management, due to an increase in animal 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 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 2018, total N_2O emissions from manure management were estimated to be 19.4 MMT CO_2 Eq. (65 kt); in 1990, emissions were 14.0 MMT CO_2 Eq. (47 kt). These values include both direct and indirect N_2O emissions from manure management. Nitrous oxide emissions have increased since 1990. Small changes in N_2O emissions from individual animal groups exhibit the same trends as the animal group populations, with the overall net effect that N_2O emissions showed a 39 percent increase from 1990 to 2018 and a 4.2 percent increase from 2017 through 2018. Overall shifts toward liquid systems have driven down the emissions per unit of nitrogen excreted as dry manure handling systems have greater aerobic conditions that promote N_2O emissions.

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

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[6] Manure management emissions from camels are not estimated for this Inventory. See Annex 5 for more information on sources and sinks of greenhouse gas emissions not included in this Inventory.

Table 5-7: CH_4 and N_2O Emissions from Manure Management (MMT CO_2 Eq.)

Gas/Animal Type	1990	2005	2014	2015	2016	2017	2018
CH_4[a]	**37.1**	**51.6**	**54.3**	**57.9**	**59.6**	**59.9**	**61.7**
Dairy Cattle	14.7	24.3	29.7	30.8	31.5	31.8	32.3
Beef Cattle	3.1	3.3	3.0	3.1	3.3	3.4	3.4
Swine	15.5	20.3	18.0	20.2	21.1	21.0	22.2
Sheep	0.2	0.1	0.1	0.1	0.1	0.1	0.1
Goats	+	+	+	+	+	+	+
Poultry	3.3	3.2	3.3	3.4	3.4	3.4	3.5
Horses	0.2	0.3	0.2	0.2	0.2	0.2	0.2
American Bison	+	+	+	+	+	+	+
Mules and Asses	+	+	+	+	+	+	+
N_2O[b]	**14.0**	**16.4**	**17.3**	**17.5**	**18.1**	**18.7**	**19.4**
Dairy Cattle	5.3	5.5	5.8	6.0	6.1	6.1	6.1
Beef Cattle	5.9	7.2	7.8	7.7	8.1	8.6	9.2
Swine	1.2	1.6	1.7	1.8	1.9	2.0	2.0
Sheep	0.1	0.3	0.3	0.3	0.3	0.3	0.3
Goats	+	+	+	+	+	+	+
Poultry	1.4	1.6	1.6	1.6	1.6	1.6	1.7
Horses	0.1	0.1	0.1	0.1	0.1	0.1	0.1
American Bison[c]	NA	NA	NA	NA	NA	NA	NA
Mules and Asses	+	+	+	+	+	+	+
Total	**51.1**	**67.9**	**71.6**	**75.4**	**77.7**	**78.5**	**81.1**

+ 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.

Notes: Emissions from manure deposited on pasture are included in the Agricultural Soils Management sector. Totals may not sum due to independent rounding.

Table 5-8: CH_4 and N_2O Emissions from Manure Management (kt)

Gas/Animal Type	1990	2005	2014	2015	2016	2017	2018
CH_4[a]	**1,485**	**2,062**	**2,172**	**2,316**	**2,385**	**2,395**	**2,467**
Dairy Cattle	589	970	1,190	1,233	1,259	1,270	1,292
Beef Cattle	126	133	120	126	132	136	135
Swine	622	812	719	808	846	840	888
Sheep	7	3	3	3	3	3	3
Goats	1	1	1	1	1	1	1
Poultry	131	129	132	136	136	137	141
Horses	9	12	8	8	8	7	7
American Bison	+	+	+	+	+	+	+
Mules and Asses	+	+	+	+	+	+	+
N_2O[b]	**47**	**55**	**58**	**59**	**61**	**63**	**65**
Dairy Cattle	18	18	20	20	20	20	21
Beef Cattle	20	24	26	26	27	29	31
Swine	4	5	6	6	6	7	7
Sheep	+	1	1	1	1	1	1
Goats	+	+	+	+	+	+	+
Poultry	5	5	5	5	5	5	6
Horses	+	+	+	+	+	+	+
American Bison[c]	NA	NA	NA	NA	NA	NA	NA

Mules and Asses	+	+	+	+	+	+	+

+ 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: Emissions from manure deposited on pasture are included in the Agricultural Soils Management sector. Totals may not sum due to independent rounding.

Methodology

The methodologies presented in IPCC (2006) form the basis of the CH_4 and N_2O emission estimates for each animal type. 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 methodology and data used to calculate CH_4 and N_2O emissions from manure management.

Methane Calculation Methods

The following inputs were used in the calculation of manure management CH_4 emissions for 1990 through 2018:

- 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;
- Volatile solids (VS) production rate (by animal type and state or United States);
- Methane producing potential (B_0) 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 2018 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 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). 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 2006). 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 2019). 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) were 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.

Nitrous Oxide Calculation Methods

The following inputs were used in the calculation of direct and indirect manure management N_2O emissions for 1990 through 2018:

- 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 rates 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 rates were assumed to be the same as NOF bulls.[7]
- All N_2O emission factors (direct and indirect) were taken from IPCC (2006). These data are appropriate because they were developed using U.S. data.
- 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 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).

Next, indirect N_2O emissions from volatilization (kg N_2O per year) were calculated by multiplying the amount of N excreted (kg per year) in each WMS by the fraction of N lost through volatilization ($Frac_{tas}$) 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, and 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.

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 2018.

Uncertainty and Time-Series Consistency

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. A normal probability distribution was assumed for each source data category. 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

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[7] The N_2O emissions from N excreted (Nex) by 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.

around which the uncertainty analysis was performed for each state. 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 2018 emission estimates.

The results of the Approach 2 quantitative uncertainty analysis are summarized in Table 5-9. Manure management CH_4 emissions in 2018 were estimated to be between 50.6 and 74.0 MMT CO_2 Eq. at a 95 percent confidence level, which indicates a range of 18 percent below to 20 percent above the actual 2018 emission estimate of 61.7 MMT CO_2 Eq. At the 95 percent confidence level, N_2O emissions were estimated to be between 16.3 and 24.1 MMT CO_2 Eq. (or approximately 16 percent below and 24 percent above the actual 2018 emission estimate of 19.4 MMT CO_2 Eq.).

Table 5-9: 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	2018 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	61.7	50.6	74.0	-18%	+20%
Manure Management	N_2O	19.4	16.3	24.1	-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 and the sum of county estimates for the full time series.

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 2018 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 5-10 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 greater 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.

Table 5-10: 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)*	Implied CH_4 Emission Factors (kg/head/year)						
		1990	2005	2014	2015	2016	2017	2018
Dairy Cattle	48-112	30.2	54.5	64.2	65.6	66.8	67.2	67.9
Beef Cattle	1-2	1.5	1.6	1.6	1.7	1.7	1.7	1.6
Swine	10-45	11.5	13.3	11.2	11.8	12.1	11.7	12.0
Sheep	0.19-0.37	0.6	0.6	0.5	0.5	0.5	0.5	0.5
Goats	0.13-0.26	0.4	0.3	0.3	0.3	0.3	0.3	0.3
Poultry	0.02-1.4	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Horses	1.56-3.13	4.3	3.1	2.5	2.6	2.6	2.6	2.6
American Bison	NA	1.8	2.0	2.0	2.1	2.1	2.1	2.1
Mules and Asses	0.76-1.14	0.9	1.0	0.9	1.0	1.0	1.0	1.0

NA (Not Applicable)

* 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

The manure management emission estimates include the following recalculations relative to the previous Inventory:

- State animal populations were updated to reflect updated USDA NASS datasets, which resulted in population changes for:
  - Poultry in 2017,
  - Market swine in 2013-2017,
  - Breeding swine in 2017, and
  - American bison, goats, horses, and mules and asses in 2013-2015 (USDA 2019a).
- Incorporated 2017 USDA Census of Agriculture data which affected animal populations (bison, goats, horses, and mules and asses), farm-level distribution data which affect WMS distributions for dairy cows and swine, and county-level temperature data which affects MCFs. These updates affected methane and nitrous oxide emissions for 2013 through 2017 (USDA 2019d).
- WMS distribution data for dairy cows were updated with data from the 2016 USDA Agricultural Resource Management Survey (ARMS) of dairy producers (ERG 2019).
- Anaerobic digestion data were updated for swine, dairy cows, and poultry using data from EPA's AgSTAR Program (EPA 2019).

These changes impacted total emission estimates for 1990 through 2017, overall decreasing annual estimations from less than 1 percent to 5.1 percent across the time series. The most significant changes were to the dairy cow emissions estimates, resulting primarily from the dairy cow WMS update. Total dairy cow annual estimations decreased throughout the entire time series, but most significantly for 2008 through 2015 during which time they decreased by over 10 percent.

Planned Improvements

Regular annual data reviews and updates are necessary to maintain an emissions inventory that reflects the current base of knowledge. EPA conducts the following list of regular annual assessments of data availability when updating the estimates to extend time series each year:

- Continuing to investigate new sources of WMS data. EPA is working with the USDA Natural Resources Conservation Service to collect data for potential improvements to the Inventory.
- Updating the B_0 data used in the Inventory, as data become available.

EPA notes that many of the improvements identified below are major updates and may take multiple years to fully implement. Potential improvements (long-term improvements) for future Inventory years include:

- Revising the methodology for population distribution to states where USDA population data are withheld due to disclosure concerns. EPA previously discussed these changes with the National Emissions Inventory staff to potentially improve consistency across U.S. inventories.
- Revising the anaerobic digestion estimates to estimate CH_4 emissions reductions due to the use of anaerobic digesters (the Inventory currently estimates only emissions from anaerobic digestion systems).
- Investigating improved emissions estimate methodologies for swine pit systems with less than one month of storage (the new swine WMS data included this WMS category).
- Comparing CH_4 and N_2O emission estimates with estimates from other models and more recent studies and compare the results to the Inventory, such as USDA's Dairy Gas Emissions Model.
- 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.
- Improving collaboration 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 they depend on each other's outputs to properly calculate emissions.
- Revising the uncertainty analysis to address changes that have been implemented to the CH_4 and N_2O estimates.
- EPA acknowledges IPCC's 2019 Refinement to *2006 IPCC Guidelines* for National Greenhouse Gas Inventories will provide updated emission factors that may affect emissions estimates for manure management. EPA will work to review these updates and incorporate changes as time and resources allow.

5.3 Rice Cultivation (CRF Source Category 3C)

Most of the world's rice is grown on flooded fields (Baicich 2013) that creates 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[8] 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). Fertilization practices also influences CH_4 emissions, particularly the use of fertilizers with sulfate (Wassmann et al. 2000b; Linquist et al. 2012), which can reduce CH_4 emissions. 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 thirteen states, including Arkansas, California, Florida, Illinois, Kentucky, Louisiana, Minnesota, Mississippi, Missouri, New York, South Carolina, 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 2016 to 2018 in this Inventory due to lack of data in the later 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 5-11, Table 5-12, and Figure 5-2). Most emissions occur in Arkansas, California, Louisiana Mississippi, Missouri and Texas. In 2018, CH_4 emissions from rice cultivation were 13.3 MMT CO_2 Eq. (533 kt). Annual emissions fluctuate between 1990 and 2018, which is largely due to differences in the amount of rice harvested areas over time, which has been decreasing over the past two decades. Consequently, emissions in 2018 are 17 percent lower than emissions in 1990.

Table 5-11: CH_4 Emissions from Rice Cultivation (MMT CO_2 Eq.)

State	1990	2005	2014	2015	2016	2017	2018
Arkansas	5.4	7.9	5.7	6.4	NE	NE	NE
California	3.3	3.4	3.9	4.1	NE	NE	NE
Florida	+	+	+	+	NE	NE	NE
Illinois	+	+	+	+	NE	NE	NE
Kentucky	+	+	+	+	NE	NE	NE
Louisiana	2.6	2.8	3.2	2.6	NE	NE	NE
Minnesota	+	0.1	+	+	NE	NE	NE

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[8] 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 and use to stimulate more production. The amount of root exudate produced by a rice plant over a growing season varies among rice varieties.

Mississippi	1.1	1.4	0.8	1.0	NE	NE	NE
Missouri	0.6	1.1	0.8	0.7	NE	NE	NE
New York	+	+	+	+	NE	NE	NE
South Carolina	+	+	+	+	NE	NE	NE
Tennessee	+	+	+	+	NE	NE	NE
Texas	3.0	1.3	0.9	1.4	NE	NE	NE
Total	**16.0**	**18.0**	**15.4**	**16.2**	**13.5**	**12.8**	**13.3**

+ Does not exceed 0.05 MMT CO_2 Eq.

NE (Not Estimated). State-level emissions are not estimated for 2016 through 2018 in this Inventory because data are unavailable. A surrogate data method is used to estimate emissions for these years and are produced only at the national scale.

Note: Totals may not sum due to independent rounding.

Table 5-12: CH_4 Emissions from Rice Cultivation (kt)

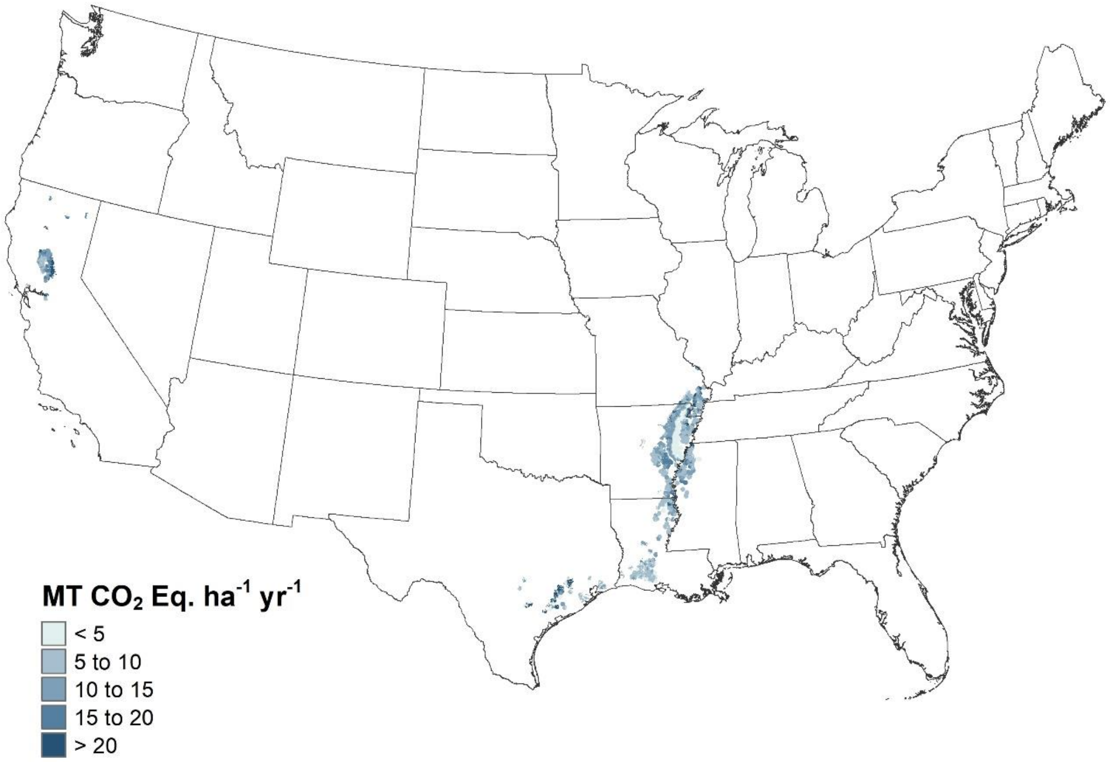
State	1990	2005	2014	2015	2016	2017	2018
Arkansas	216	315	229	256	NE	NE	NE
California	131	135	155	166	NE	NE	NE
Florida	+	1	+	+	NE	NE	NE
Illinois	+	+	+	+	NE	NE	NE
Kentucky	+	+	+	+	NE	NE	NE
Louisiana	103	113	130	103	NE	NE	NE
Minnesota	1	2	+	+	NE	NE	NE
Mississippi	45	55	31	40	NE	NE	NE
Missouri	22	45	34	26	NE	NE	NE
New York	+	+	+	+	NE	NE	NE
South Carolina	+	+	+	+	NE	NE	NE
Tennessee	+	+	+	+	NE	NE	NE
Texas	122	54	37	57	NE	NE	NE
Total	**640**	**720**	**616**	**648**	**539**	**510**	**533**

+ Does not exceed 0.5 kt.

NE (Not Estimated). State-level emissions are not estimated for 2016 through 2018 in this Inventory because data are unavailable. A surrogate data method is used to estimate emissions for these years and are produced only at the national scale.

Note: Totals may not sum due to independent rounding.

Figure 5-2: Annual CH_4 Emissions from Rice Cultivation, 2015 (MT CO_2 Eq./Year)



Note: Only national-scale emissions are estimated for 2016 through 2018 in this Inventory using the surrogate data method described in the Methodology section; therefore, the fine-scale emission patterns in this map are based on the estimates for 2015.

Methodology

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 a process-based model (DayCent) 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 simulates 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 C 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 crops and rotations, land uses, as well as organic soils or cobbly, gravelly, and shaley mineral soils.

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, ratooning, etc.). The Tier 1 analysis is implemented in the Agriculture and Land Use National Greenhouse Gas Inventory (ALU) software (Ogle et al. 2016).[9]

Rice cultivation areas are based on cropping and land use histories recorded in the USDA National Resources Inventory (NRI) survey (USDA-NRCS 2018). The NRI is a statistically-based sample of all non-federal land, and includes 489,178 survey locations in agricultural land for the conterminous United States and Hawaii of which 1,960 include one or more years of rice cultivation. The Tier 3 method is used to estimate CH_4 emissions from 1,655 of the NRI survey locations, and the remaining 305 survey locations are estimated with the Tier 1 method. Each NRI survey location is associated with an "expansion factor" that allows scaling of CH_4 emission to the entire country (i.e., each expansion factor represents 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 4 out of 5 years for each 5-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 currently available through 2015 (USDA-NRCS 2018). The current Inventory only uses NRI data through 2015 because newer data are not available, but will be incorporated when additional years of data are released by USDA-NRCS. The harvested rice areas in each state are presented in Table 5-13.

Table 5-13: Rice Area Harvested (1,000 Hectares)

State/Crop	1990	2005	2014	2015	2016	2017	2018
Arkansas	600	784	700	679	NE	NE	NE
California	249	236	257	280	NE	NE	NE
Florida	0	4	0	0	NE	NE	NE
Illinois	0	0	0	0	NE	NE	NE
Kentucky	0	0	0	0	NE	NE	NE
Louisiana	381	402	375	368	NE	NE	NE
Minnesota	4	9	1	1	NE	NE	NE
Mississippi	123	138	92	98	NE	NE	NE
Missouri	48	94	93	62	NE	NE	NE
New York	1	0	0	0	NE	NE	NE
South Carolina	0	0	0	0	NE	NE	NE
Tennessee	0	1	0	0	NE	NE	NE
Texas	302	118	112	131	NE	NE	NE
Total	**1,707**	**1,788**	**1,631**	**1,619**	**NE**	**NE**	**NE**

NE (Not Estimated). State-level area data are not available for 2016 through 2018 but will be added in a future Inventory with release of new NRI survey data.
Note: Totals may not sum due to independent rounding.

The Southeastern states have sufficient growing periods for a ratoon crop in some years. For example, the growing season length is occasionally sufficient for ratoon crops to be grown on about 1 percent of the rice fields in Arkansas. No data are available about ratoon crops in Missouri or Mississippi, and 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. Ratooned crop area as a percent of primary crop area is presented in Table 5-14.

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[9] See <http://www.nrel.colostate.edu/projects/ALUsoftware/>.

Table 5-14: Average Ratooned Area as Percent of Primary Growth Area (Percent)

State	1990-2015
Arkansas[a]	1%
California	0%
Florida[b]	49%
Louisiana[c]	32%
Mississippi[a]	1%
Missouri[a]	1%
Texas[d]	45%

[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 method. Variation in flooding can be incorporated in future Inventories if water management data are collected.

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.

A surrogate data method is used to estimate emissions from 2016 to 2018 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 the 1990 through 2015 emissions data that were derived using the Tier 1 and 3 methods (Brockwell and Davis 2016). Surrogate data for this model are based on rice commodity statistics from USDA-NASS.[10] See Box 5-2 for more information about the surrogate data method.

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 due to the fact that 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 2015 emissions data that has

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[10] See <https://quickstats.nass.usda.gov/>.

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), Xβ 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. Parameters are estimated from the observed data for 1990 to 2015 using standard statistical techniques, and these estimates are used to predict the missing emissions data for 2016 to 2018.

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 2015).

Uncertainty and Time-Series Consistency

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. A Monte Carlo analysis was used to propagate uncertainties in the Tier 1 and 3 methods. For 2016 to 2018, 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 2018 were estimated to be between 9.2 and 21.6 MMT CO_2 Eq. at a 95 percent confidence level, which indicates a range of 31 percent below to 62 percent above the 2018 emission estimate of 13.3 MMT CO_2 Eq. (see Table 5-15).

Table 5-15: Approach 2 Quantitative Uncertainty Estimates for CH_4 Emissions from Rice Cultivation (MMT CO_2 Eq. and Percent)

Source	Inventory Method	Gas	2018 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	10.8	6.9	14.8	-36%	+36%
Rice Cultivation	Tier 1	CH_4	2.5	1.3	3.7	-48%	+48%
Rice Cultivation	**Total**	**CH_4**	**13.3**	**9.2**	**21.6**	**-31%**	**+62%**

[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. 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. Two errors were found in the spreadsheets. First, CH_4 emissions from rice cultivation were not included in the national totals due to an incorrect formula. Second, the amount of residue returned to the field was estimated in units of C, but should be in units of dry matter. Both errors were corrected.

Model results are compared to field measurements to verify if 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, 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

Methodological recalculations are applied to the entire time-series to ensure time-series consistency from 1990 through 2017. The major improvements were (1) incorporating new land use and crop histories from the NRI survey; and (2) modeling SOC stock changes to 30 cm depth with the Tier 3 approach (previously modeled to 20 cm depth), which impacts the simulation of methanogenesis in DayCent. The surrogate data method was also applied to re-estimate stock changes from 2016 to 2017. These changes resulted in an average increase in rice cultivation CH_4 emissions of 1.2 MMT CO_2 Eq. from 1990 to 2018, which is an average of 9 percent larger compared to the previous Inventory.

Planned Improvements

A key planned improvement for rice cultivation is to fill several gaps in the management activity including compiling new data on water management, organic amendments and ratooning practices in rice cultivation systems. This improvement is expected to be completed for the next Inventory, but the timeline may be extended if there are insufficient resources to fund this improvement.

5.4 Agricultural Soil Management (CRF 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).[11] Mineral N is made available in soils through decomposition of soil organic matter and plant litter, as well as asymbiotic fixation of N from the atmosphere.[12] Several agricultural activities increase mineral N availability in soils that lead to direct N_2O emissions at the site of a management activity (see Figure 5-3) (Mosier et al. 1998). These activities include synthetic N fertilization; application of managed livestock manure; application of other organic materials such as biosolids (i.e., sewage sludge); deposition of manure on soils by domesticated animals in pastures, range, and paddocks (PRP) (i.e., unmanaged manure); retention of crop residues (N-fixing legumes and non-legume crops and

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[11] 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 denitrification, which leaks from microbial cells into the soil and then into the atmosphere. Nitrous oxide is also produced during nitrification, although by a less well-understood mechanism (Nevison 2000).

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

forages); and drainage of organic soils[13] (i.e., Histosols) (IPCC 2006). Additionally, agricultural soil management activities, including irrigation, drainage, tillage practices, cove crops, and fallowing of land, can influence N mineralization from soil organic matter and levels of asymbiotic N fixation. Indirect emissions of N_2O occur when N 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 N, and (2) surface runoff and leaching of applied/mineralized N into groundwater and surface water.[14] Direct and indirect emissions from agricultural lands are included in this section (i.e., cropland and grassland as defined in Section 6.1 Representation of the U.S. Land Base). Nitrous oxide emissions from Forest Land and Settlements soils are found in Sections 6.2 and 6.10, respectively.

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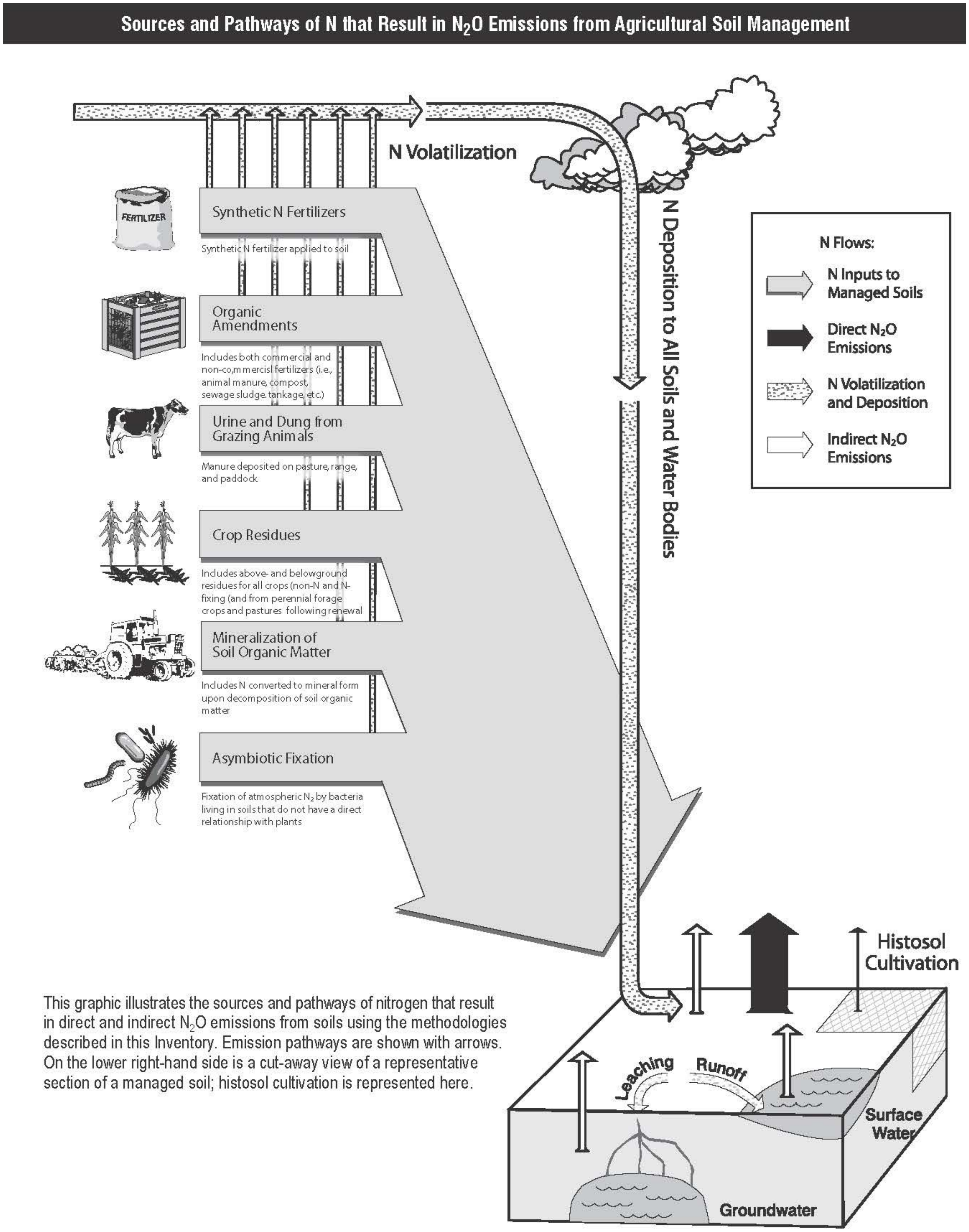
[13] Drainage of organic soils in former wetlands enhances mineralization of N-rich organic matter, thereby increasing N_2O emissions from these soils.

[14] These processes entail volatilization of applied or mineralized N as NH_3 and NO_x, transformation of these gases in the atmosphere (or upon deposition), and deposition of the N 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 N inputs from terrestrial systems in order to avoid double-counting.

Figure 5-3: Sources and Pathways of N that Result in N_2O Emissions from Agricultural Soil Management



This graphic illustrates the sources and pathways of nitrogen that result in direct and indirect N_2O emissions from soils using the methodologies described in this Inventory. Emission pathways are shown with arrows. On the lower right-hand side is a cut-away view of a representative section of a managed soil; histosol cultivation is represented here.

Agricultural soils produce the majority of N_2O emissions in the United States. Estimated emissions in 2018 are 338.2 MMT CO_2 Eq. (1,135 kt) (see Table 5-16 and Table 5-17). Annual N_2O emissions from agricultural soils are 7 percent greater in the 2018 compared to 1990, but emissions fluctuated between 1990 and 2018 due to inter-annual variability largely associated with weather patterns, synthetic fertilizer use, and crop production. From 1990 to 2018, cropland accounted for 68 percent of total direct emissions on average, 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 5-18 and Table 5-19.

Table 5-16: N_2O Emissions from Agricultural Soils (MMT CO_2 Eq.)

Activity	1990	2005	2014	2015	2016	2017	2018
Direct	**272.5**	**272.2**	**302.3**	**294.5**	**281.0**	**280.0**	**285.7**
Cropland	185.9	184.1	207.6	200.2	191.6	191.3	196.0
Grassland	86.6	88.1	94.6	94.3	89.4	88.7	89.7
Indirect	**43.4**	**40.8**	**47.0**	**53.6**	**48.8**	**47.4**	**52.5**
Cropland	34.2	31.8	37.9	43.0	39.2	37.8	42.8
Grassland	9.2	9.1	9.1	10.6	9.6	9.6	9.7
Total	**315.9**	**313.0**	**349.2**	**348.1**	**329.8**	**327.4**	**338.2**

Notes: Estimates after 2015 are based on a data splicing method (See Methodology section). Totals may not sum due to independent rounding.

Table 5-17: N_2O Emissions from Agricultural Soils (kt)

Activity	1990	2005	2014	2015	2016	2017	2018
Direct	**915**	**914**	**1,014**	**988**	**943**	**939**	**959**
Cropland	623.8	617.7	696.8	671.8	642.9	641.9	657.7
Grassland	290.7	295.8	317.5	316.4	300.0	297.5	300.9
Indirect	**146**	**137**	**158**	**180**	**164**	**159**	**176**
Cropland	114.8	106.6	127.1	144.2	131.5	126.9	143.5
Grassland	30.7	30.4	30.5	35.6	32.3	32.2	32.6
Total	**1,060**	**1,050**	**1,172**	**1,168**	**1,107**	**1,099**	**1,135**

Notes: Estimates after 2015 are based on a data splicing method (See Methodology section). Totals may not sum due to independent rounding.

Table 5-18: Direct N_2O Emissions from Agricultural Soils by Land Use Type and N Input Type (MMT CO_2 Eq.)

Activity	1990	2005	2014	2015	2016	2017	2018
Cropland	**185.8**	**184.0**	**207.6**	**200.2**	**191.6**	**191.3**	**196.0**
Mineral Soils	**182.1**	**180.3**	**204.2**	**196.8**	**188.2**	**187.9**	**192.6**
Synthetic Fertilizer	63.1	64.0	70.5	64.8	60.8	60.5	61.8
Organic Amendment[a]	12.6	13.4	14.2	14.1	14.1	14.0	14.0
Residue N[b]	39.3	39.6	42.4	39.0	37.7	37.7	38.7
Mineralization and Asymbiotic Fixation	67.1	63.3	77.1	78.9	75.5	75.7	78.1
Drained Organic Soils	**3.8**	**3.7**	**3.4**	**3.4**	**3.4**	**3.4**	**3.4**
Grassland	**86.7**	**88.2**	**94.6**	**94.3**	**89.4**	**88.7**	**89.7**
Mineral Soils	**84.2**	**85.8**	**92.2**	**91.8**	**86.9**	**86.2**	**87.2**
Synthetic Fertilizer	+	+	+	+	+	+	+
PRP Manure	14.6	12.8	11.6	11.6	11.3	11.2	11.3
Managed Manure[c]	+	+	+	+	+	+	+
Biosolids (i.e., Sewage Sludge)	0.2	0.5	0.6	0.6	0.6	0.6	0.6
Residue N[d]	29.7	30.8	31.8	30.4	28.6	28.4	28.7
Mineralization and Asymbiotic Fixation	39.5	41.7	48.2	49.2	46.3	45.9	46.5

Drained Organic Soils	**2.5**	**2.4**	**2.5**	**2.5**	**2.5**	**2.5**	**2.5**
Total	**272.5**	**272.2**	**302.3**	**294.5**	**281.0**	**280.0**	**285.7**

[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 N inputs include N in unharvested legumes as well as crop residue N.

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

[d] Grassland residue N inputs include N in ungrazed legumes as well as ungrazed grass residue N.

Notes: Estimates after 2015 are based on a data splicing method (See Methodology section). Totals may not sum due to independent rounding.

+ Does not exceed 0.05 MMT CO_2 Eq.

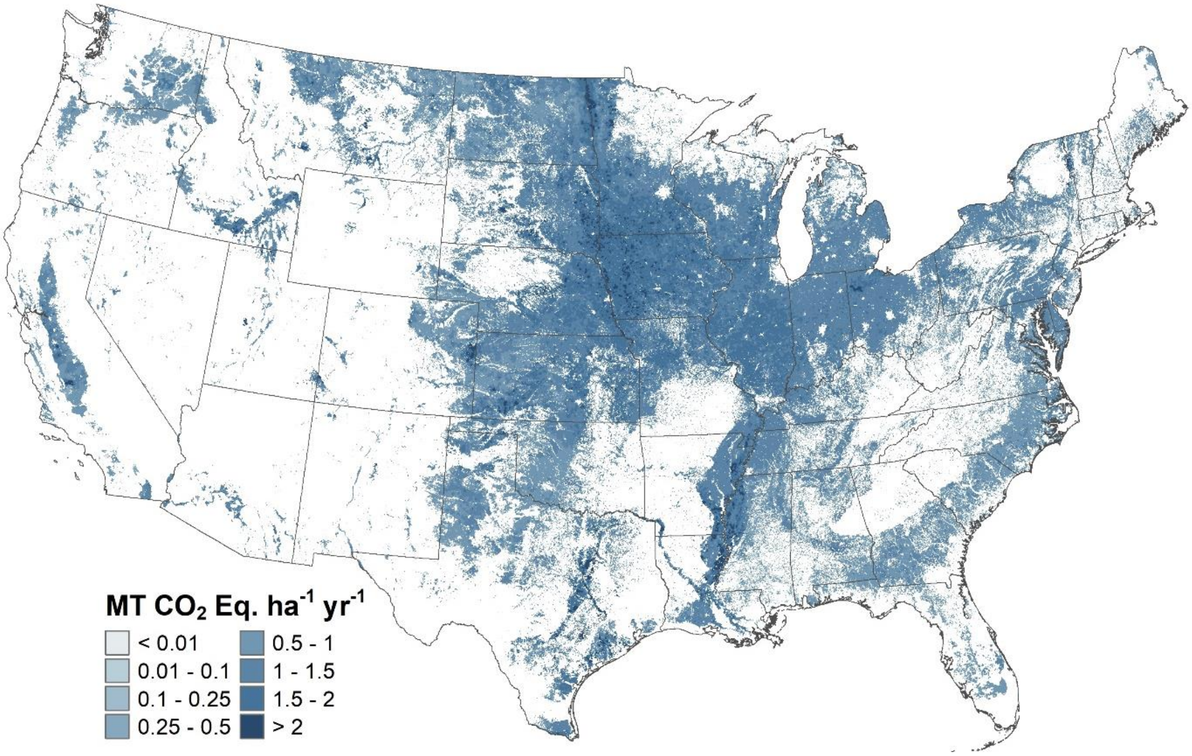
Table 5-19: Indirect N_2O Emissions from Agricultural Soils (MMT CO_2 Eq.)

Activity	1990	2005	2014	2015	2016	2017	2018
Cropland	**34.2**	**31.8**	**37.9**	**43.0**	**39.2**	**37.8**	**42.8**
Volatilization & Atm. Deposition	6.5	7.3	8.2	8.6	8.3	8.1	8.2
Surface Leaching & Run-Off	27.7	24.4	29.7	34.4	30.9	29.7	34.6
Grassland	**9.2**	**9.1**	**9.1**	**10.6**	**9.6**	**9.6**	**9.7**
Volatilization & Atm. Deposition	3.6	3.6	3.6	3.5	3.4	3.4	3.4
Surface Leaching & Run-Off	5.6	5.5	5.5	7.1	6.3	6.2	6.3
Total	**43.4**	**40.8**	**47.0**	**53.6**	**48.8**	**47.4**	**52.5**

Notes: Estimates after 2015 are based on a data splicing method (See Methodology section). Totals may not sum due to independent rounding.

Figure 5-4 and Figure 5-5 show regional patterns for direct N_2O emissions. Figure 5-6 and Figure 5-7 show indirect N_2O emissions from volatilization, and Figure 5-8 and Figure 5-9 show the indirect N_2O emissions from leaching and runoff in croplands and grasslands, respectively.

Figure 5-4: Crops, 2015 Annual Direct N_2O Emissions Estimated Using the Tier 3 DayCent Model (MT CO_2 Eq./ha/year)

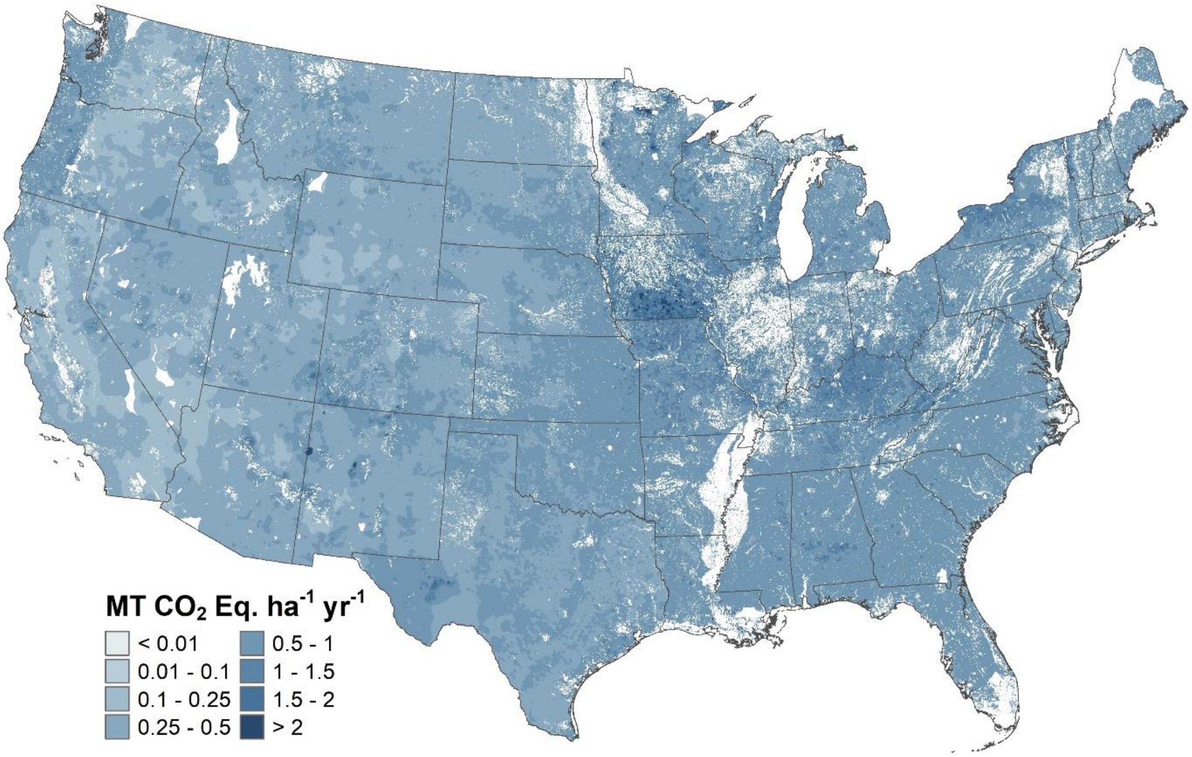


Note: Only national-scale emissions are estimated for 2016 to 2018 using a splicing method, and therefore the fine-scale emission patterns in this map are based on Inventory data from 2015.

Direct N_2O emissions from croplands occur throughout all of the cropland regions but tend to be high in the Midwestern Corn Belt Region (Illinois, Iowa, Indiana, Ohio, southern Minnesota and Wisconsin, and eastern Nebraska), where a large portion of the land is used for growing highly fertilized corn and N-fixing soybean crops (see Figure 5-4). Kansas, South Dakota and North Dakota have relatively high emissions from large areas of crop production that are found in the Great Plains region. 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 through Nebraska, Snake River Valley in Idaho and the Central Valley in California. Direct emissions are low in many parts of the eastern United States because only a small portion of land is cultivated, and in many western states where rainfall and access to irrigation water are limited.

Direct emissions from grasslands are highest from states in the Great Plains and western United States (see Figure 5-5) where a high proportion of the land is dominated by grasslands and used for cattle and sheep grazing. However, there are relatively large emissions from local areas in the Southeast, particularly Kentucky, Florida and Tennessee, in addition to areas in Missouri and Iowa, where there can be higher rates of Pasture/Range/Paddock (PRP) manure N additions on a relatively small amount of pasture due to greater stocking rates of livestock per unit of area, compared to other regions of the United States.

Figure 5-5: Grasslands, 2015 Annual Direct N_2O Emissions Estimated Using the Tier 3 DayCent Model (MT CO_2 Eq./ha/year)

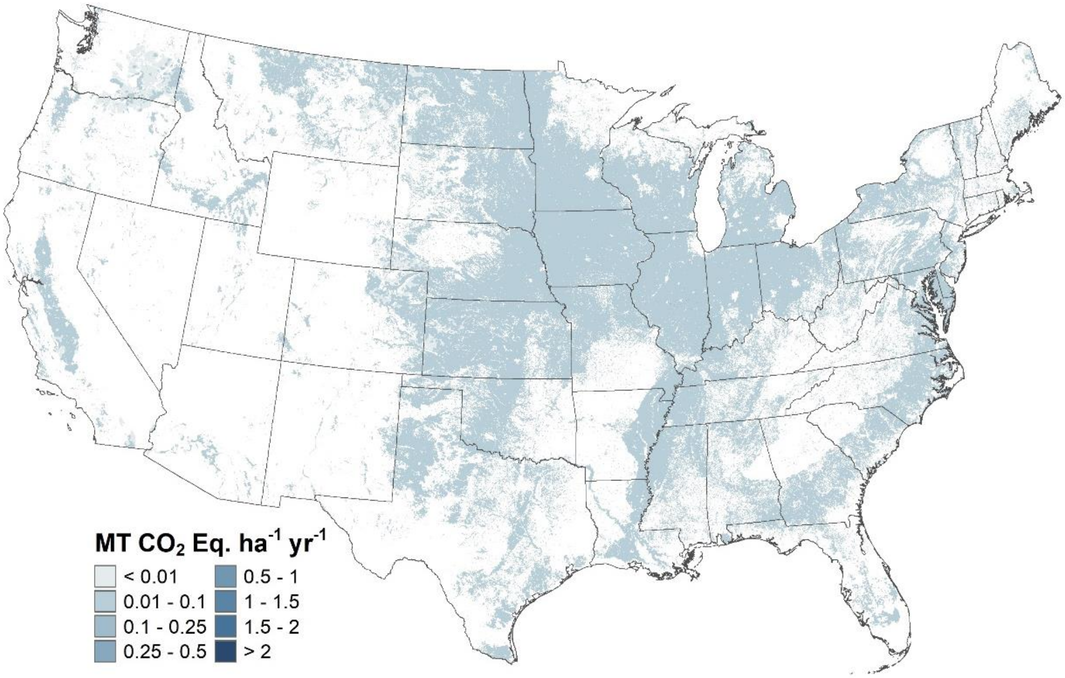


Note: Only national-scale emissions are estimated for 2016 to 2018 using a splicing method, and therefore the fine-scale emission patterns in this map are based on Inventory data from 2015.

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 and Great Plains. Indirect N_2O emissions from volatilization in grasslands are higher in the Southeastern United States, along with portions of the Mid-Atlantic and southern Iowa. The higher emissions in this region are mainly due to large additions of PRP manure N on relatively small but productive pastures that support intensive grazing, which in turn, stimulates NH_3 volatilization.

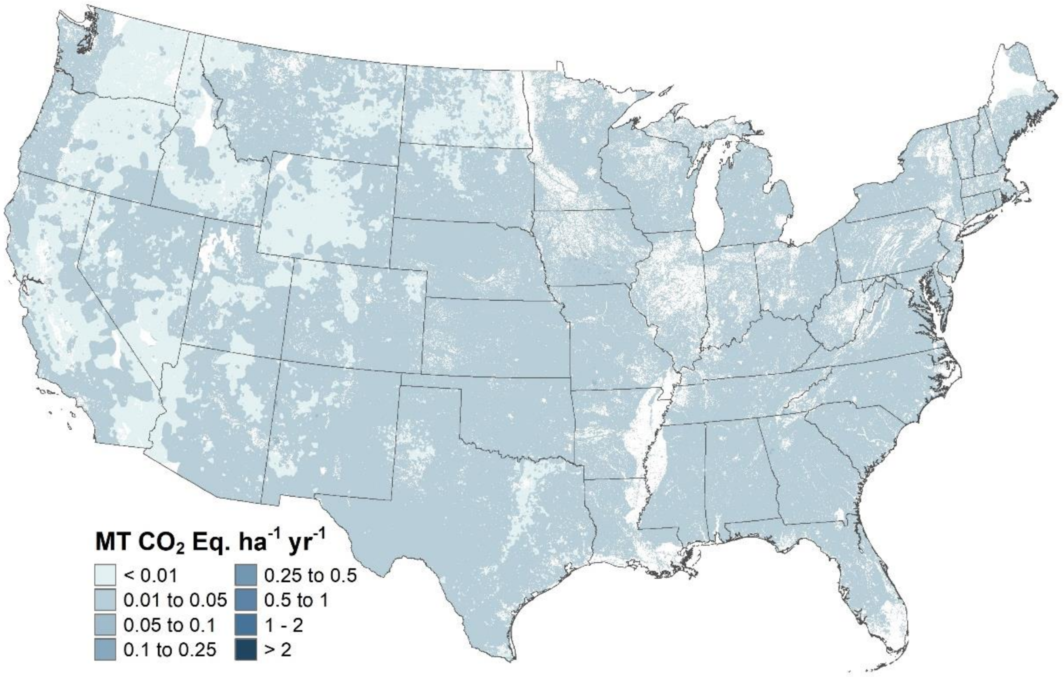
Indirect N_2O emissions from surface runoff and leaching of applied/mineralized N in croplands is highest in the Midwestern Corn Belt. There are also relatively high emissions associated with N management in the Lower Mississippi River Basin, Piedmont region of the Southeastern United States and the Mid-Atlantic states. In additions, small areas of high emissions occur in portions of the Great Plains that have relatively large areas of irrigated croplands that can have relatively high leaching rates of applied/mineralized N. Indirect N_2O emissions from surface runoff and leaching of applied/mineralized N 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 5-6: Crops, 2015 Annual Indirect N_2O Emissions from Volatilization Using the Tier 3 DayCent Model (MT CO_2 Eq./ha/year)



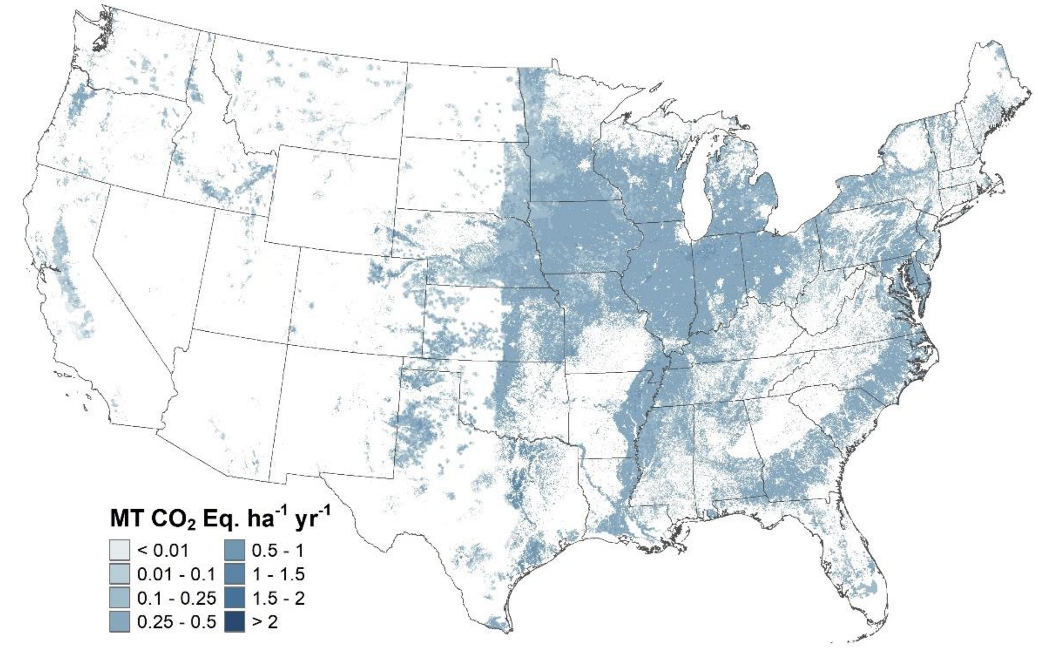
Note: Only national-scale emissions are estimated for 2016 to 2018 using a splicing method, and therefore the fine-scale emission patterns in this map are based on Inventory data from 2015.

Figure 5-7: Grasslands, 2015 Annual Indirect N_2O Emissions from Volatilization Using the Tier 3 DayCent Model (MT CO_2 Eq./ha/year)



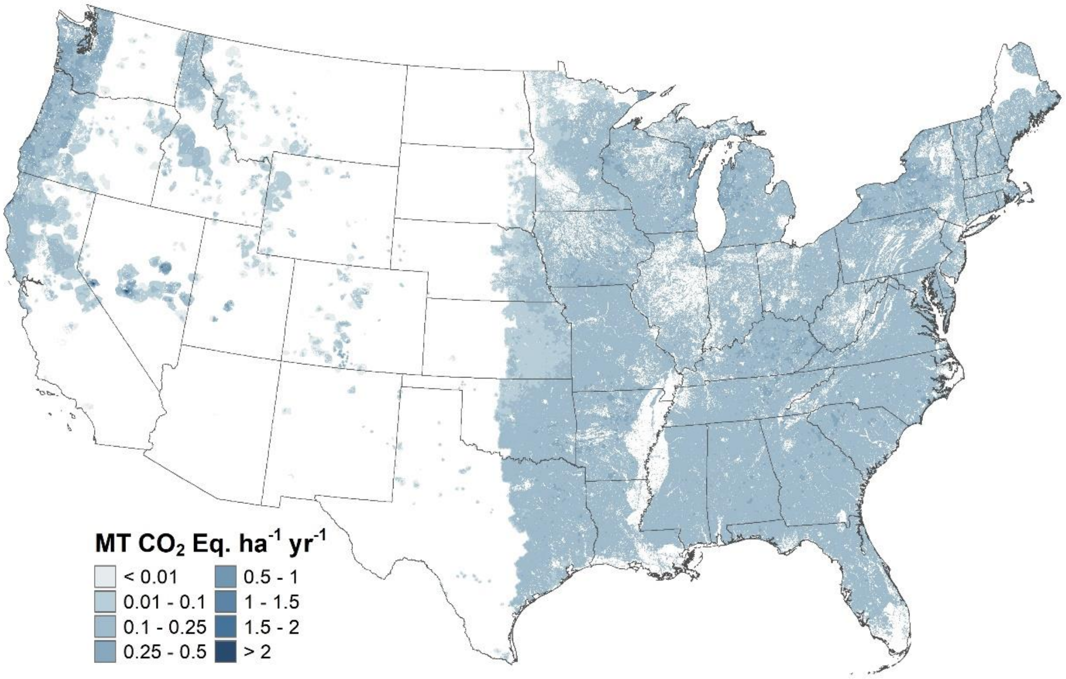
Note: Only national-scale emissions are estimated for 2016 to 2018 using a splicing method, and therefore the fine-scale emission patterns in this map are based on Inventory data from 2015.

Figure 5-8: Crops, 2015 Annual Indirect N_2O Emissions from Leaching and Runoff Using the Tier 3 DayCent Model (MT CO_2 Eq./ha/year)



Note: Only national-scale emissions are estimated for 2016 to 2018 using a splicing method, and therefore the fine-scale emission patterns in this map are based on Inventory data from 2015.

Figure 5-9: Grasslands, 2015 Annual Indirect N_2O Emissions from Leaching and Runoff Using the Tier 3 DayCent Model (MT CO_2 Eq./ha/year)



Note: Only national-scale emissions are estimated for 2016 to 2018 using a splicing method, and therefore the fine-scale emission patterns in this map are based on Inventory data from 2015.

Methodology

The *2006 IPCC Guidelines* (IPCC 2006) divide emissions from the agricultural soil management source category into five components, including (1) direct emissions from N additions to cropland and grassland mineral soils from synthetic fertilizers, biosolids (i.e., sewage sludge) applications, crop residues (legume N-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 N additions and manure deposition to soils that lead to volatilization, leaching, or runoff of N 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 consistent with the managed land concept (IPCC 2006), including direct and indirect N_2O emissions from asymbiotic fixation[15] and mineralization of N 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.

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) where data are not yet available. 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 biosolids (i.e., sewage sludge) amendments (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 C stock changes from mineral cropland soils in a single analysis. Carbon and N 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 C 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 C and N cycling in soils.

The Tier 3 approach is based on the crop and land use histories recorded in the USDA National Resources Inventory (NRI) (USDA-NRCS 2018a). The NRI is a statistically-based sample of all non-federal land,[16] and includes 349,464 points 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 average of 175,527 locations in the NRI survey across the time series, which are designated as cropland or grassland (discussed later in this section). Each survey location is associated with an "expansion factor" that allows scaling of N_2O emissions from NRI points to the entire country (i.e., each expansion factor represents 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 2015 (USDA-NRCS 2018a).

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

[16] The NRI survey does include sample points on federal lands, but the program does not collect data from those sample locations.

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 N inputs (i.e., synthetic fertilizer, manure, N 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 N 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 N inputs, land use and management, as well as environmental conditions at specific locations, such as freeze-thaw effects that generate hot moments of N_2O emissions (Wagner-Riddle et al. 2017). 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 N 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 N cycling. Tier 1 assumes that N 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 is likely to create bias in estimated N_2O emissions for a specific year. In contrast, the process-based model used in the Tier 3 approach includes the legacy effect of N 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, grass hay, grass-clover hay, oats, peanuts, potatoes, rice, sorghum, soybeans, sugar beets, sunflowers, tobacco and wheat, but is not applied to estimate N_2O emissions from other crops or rotations with other crops,[17] such as sugarcane, some vegetables, tobacco, 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 N inputs for crops on mineral soils that are not simulated by DayCent; (2) direct emissions from PRP N additions on federal grasslands; (3) direct emissions for land application of biosolids (i.e., 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 from 2016 to 2018 at the national scale because new NRI activity data are not available 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 2015 emissions that are derived using the Tier 3 method. Surrogate data for these regression models includes corn and soybean yields from USDA-NASS statistics,[18] and weather data from the PRISM Climate Group (PRISM 2018). For the Tier 1 method, a linear-time series model is used to estimate emissions from 2016 to

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[17] 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.

[18] See <https://quickstats.nass.usda.gov/>.

2018 without surrogate data. See Box 5-4 for more information about the splicing method. Emission estimates for 2016 to 2018 will be recalculated in future Inventory reports when new NRI data are available.

Box 5-4: Surrogate Data Method

An approach to extend the time series is needed for Agricultural Soil Management because there are typically 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 modeled 1990 to 2015 emissions data, which 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., 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 from the emissions data for 1990 to 2015 using standard statistical techniques, and these estimates are used in the model described above to predict the missing emissions data for 2016 to 2018.

A critical issue when applying splicing methods is to account for the additional uncertainty introduced by predicting emissions with related information 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 from 1990 to 2015). 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 from 2016 to 2018. 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 2015 NRI (USDA-NRCS 2018a). 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[19] (Potter et al. 1993, 2007). The model simulates soil temperature, and water dynamics, using daily weather data using a 4-kilometer gridded product developed by the PRISM Climate Group (2018), and

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[19] NPP 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 2015. 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.

soil attributes from the Soil Survey Geographic Database (SSURGO) (Soil Survey Staff 2019). DayCent is used to estimate direct N_2O emissions due to mineral N available from the following sources: (1) application of synthetic fertilizers; (2) application of livestock manure; (3) retention of crop residues in the field for N-fixing legumes and non-legume crops and subsequent mineralization of N during microbial decomposition (i.e., leaving residues in the field after harvest instead of burning or collecting residues); (4) mineralization of N 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 2018b; USDA-NRCS 2012). CEAP data are collected at a subset of NRI survey locations, and currently provide management information from approximately 2002 to 2006. These data are combined with other datasets in an imputation analysis that extend the time series from 1990 to 2015. 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 an artificial neural network to determine the likely management practice at a given NRI survey location (Cheng and Titterington 1994), and c) assign management practices from the CEAP survey to specific NRI locations using predictive mean matching methods that are adapted to reflect the trending information (Little 1988, van Buuren 2012). The artificial neural network is a machine learning method that approximates nonlinear functions of inputs and searches through a very large class of models to impute an initial value for management practices at specific NRI survey locations. The predictive mean matching method identifies the most similar management activity recorded in the CEAP survey that matches the prediction from the artificial neural network. 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 artificial neural network. There are six complete imputations of the management activity data using these methods.

To determine trends in mineral fertilization and manure amendments from 1979 to 2015, 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 2018). Additional data on fertilization practices are compiled through other sources particularly the National Agricultural Statistics Service (USDA-NASS 1992, 1999, 2004). The donor survey data from CEAP contain both mineral fertilizer rates and manure amendment rates, so that the selection of a donor via predictive mean matching yields the joint imputation of both rates. This approach captures the relationship between mineral fertilization and manure amendment practices for U.S. croplands based directly on the observed patterns in the CEAP survey data.

To determine the trends in tillage management from 1979 to 2015, CEAP data are combined with Conservation Technology Information Center data between 1989 and 2004 (CTIC 2004) and USDA-ERS Agriculture Resource Management Surveys (ARMS) data from 2002 to 2015 (Claasen et al. 2018). The CTIC data are adjusted for long-term adoption of no-till agriculture (Towery 2001). It is assumed that the majority of agricultural lands are managed with full tillage prior to 1985.

For cover crops, CEAP data are combined with information from 2011 to 2016 in the USDA Census of Agriculture (USDA-NASS 2012, 2017). 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 N and N mineralized from soil organic matter as activity data. However, they are not treated as activity data in DayCent simulations because residue production, symbiotic N fixation (e.g., legumes), mineralization of N from soil organic matter, and asymbiotic N fixation are internally generated by the model as part of the simulation. In other words, DayCent accounts for the influence of symbiotic N fixation, mineralization of N from soil organic matter and crop residue retained in the field, and asymbiotic N 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 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 C and N dynamics in the DayCent model parameters and algorithms; and sampling uncertainty associated with the statistical design of the NRI survey. To assess input uncertainty, C and N 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). Sampling uncertainty is assessed using NRI replicate sampling weights. These data are combined in a Monte Carlo stochastic simulation with 1,000 iterations for 1990 through 2015. For each iteration, there is a random selection of management data from the imputation product (select one of the six imputations), random selection of parameter values and random effects for the linear mixed-effect model (i.e., structural uncertainty estimator), and random selection of a set of survey weights from the replicates associated with the NRI survey design.

Nitrous oxide emissions and 95 percent confidence intervals are estimated for each year between 1990 and 2015 using the DayCent model. However, note that 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. 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). Further elaboration on the methodology and data used to estimate N_2O emissions from mineral soils are described in Annex 3.12.

For the Tier 3 method, soil N_2O emissions from 2016 to 2018 associated with mineral soils in croplands are estimated using a splicing method that accounts for uncertainty in the original inventory data and the splicing method (See Box 5-4). Annual data are currently available through 2015 (USDA-NRCS 2018a), and the Inventory time series will be updated in the future when new NRI data are released.

Nitrous oxide emissions from managed agricultural lands are the result of interactions among anthropogenic activities (e.g., N fertilization, manure application, tillage) and other driving variables, such as weather and soil characteristics. These factors influence key processes associated with N dynamics in the soil profile, including immobilization of N 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 mineral N added to the soil, or made available through decomposition of soil organic matter and plant litter, as well as asymbiotic fixation of N from the atmosphere, is determined for each N source and then divided by the total amount of mineral N in the soil according to the DayCent model simulation. The percentages are then multiplied by the total of direct N_2O emissions in order to approximate the portion attributed to N management practices. This approach is only an approximation because it assumes that all N 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 N, 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 N.

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 N 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.[20] 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 N 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 2015, county-level fertilizer used on-farms is adjusted based on annual fluctuations in total U.S. fertilizer sales (AAPFCO 2013 through 2017).[21] The fertilizer sales for 2015 will be updated when data are released. After subtracting the portion of fertilizer applied to crops and grasslands simulated by DayCent (see Tier 3 Approach for Mineral Cropland Soils and Direct N_2O Emissions from Grassland Soils sections for information on data sources), the remainder of the total fertilizer used on farms is assumed to be applied to crops that are not simulated by DayCent.
- Similarly, a process-of-elimination approach is used to estimate manure N 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 3.10). The amount of manure N applied in the Tier 3 approach to crops and grasslands is subtracted from total annual manure N 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, which are converted to units of N using average organic fertilizer N content (TVA 1991 through 1994; AAPFCO 1995 through 2017). Commercial fertilizers do include some manure and biosolids (i.e., sewage sludge), but the amounts are removed from the commercial fertilizer data to avoid double counting with the manure N dataset described above and the biosolids (i.e., sewage sludge) amendment data discussed later in this section.
- Crop residue N is derived by combining amounts of above- and below-ground biomass, which are determined based on NRI crop area data (USDA-NRCS 2018a), crop production yield statistics (USDA-NASS 2019), dry matter fractions (IPCC 2006), linear equations to estimate above-ground biomass given dry matter crop yields from harvest (IPCC 2006), ratios of below-to-above-ground biomass (IPCC 2006), and N contents of the residues (IPCC 2006). N inputs from residue were reduced by 3 percent to account for average residue burning portions in the United States.

The total increase in soil mineral N from applied fertilizers and crop residues is 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.

Soil N_2O emissions from 2016 to 2018 for Tier 1 mineral soil emissions are estimated using a splicing method that is described in Box 5-4. As with the Tier 3 method, the time series that is based on the splicing methods will be recalculated in a future Inventory report when updated activity data are available.

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[20] Commercial organic fertilizers include dried blood, tankage, compost, and other, but the dried manure and biosolids (i.e., sewage sludge) is removed from the dataset in order to avoid double counting with other datasets that are used for manure N and biosolids.

[21] 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).

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 2015 NRI (USDA-NRCS 2018a) using soils data from the Soil Survey Geographic Database (SSURGO) (Soil Survey Staff 2019). Temperature data from the PRISM Climate Group (PRISM 2018) are 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). Annual NRI data are only available between 1990 and 2015, but the time series was adjusted using data from the Forest Inventory and Analysis Program (USFS 2019) in order to estimate emissions from 2016 to 2018. Further elaboration on the methodology and data used to estimate N_2O emissions from organic soils are described in Annex 3.12.

Tier 1 and 3 Approaches for Direct N_2O Emissions from Grassland Soils

As with N_2O emissions from croplands, the Tier 3 process-based DayCent model and Tier 1 method described in IPCC (2006) are combined to estimate emissions from non-federal grasslands and PRP manure N additions for federal grasslands, respectively. Grassland includes pasture and rangeland that produce grass or mixed grass/legume forage primarily for livestock grazing. Rangelands are typically extensive areas of native grassland that are not intensively managed, while pastures are typically 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 2018a) on non-federal grasslands resulting from manure deposited by livestock directly onto pastures and rangelands (i.e., PRP manure), N 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 N inputs are simulated within the DayCent framework, including N input from mineralization due to decomposition of soil organic matter and N inputs from senesced grass litter, as well as asymbiotic fixation of N from the atmosphere. The simulations used the same weather, soil, and synthetic N fertilizer data as discussed under the Tier 3 Approach in the Mineral Cropland Soils section. Mineral N 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 N fixation is simulated within DayCent, and therefore is not an input to the model.

Manure N deposition from grazing animals in PRP systems (i.e., PRP manure N) is a key input of N to grasslands. The amounts of PRP manure N applied on non-federal grasslands for each NRI survey location are based on the amount of N excreted by livestock in PRP systems based on the methods described in Manure Management section (Section 5.2) and associated annex (Annex 3.10). The total amount of N excreted in each county is divided by the grassland area to estimate the N input rate associated with PRP manure. The resulting input rates are used in the DayCent simulations. DayCent simulations of non-federal grasslands accounted for approximately 77 percent of total PRP manure N in aggregate across the country.[22] The remainder of the PRP manure N 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., sewage sludge) are assumed to be applied on grasslands because of the heavy metal content and other pollutants in human waste that limit its use as an amendment to croplands. Biosolids application is estimated from data compiled by EPA (1993, 1999, 2003), McFarland (2001), and NEBRA (2007) (see Section 7.2 Wastewater Treatment for a detailed discussion of the methodology for estimating sewage sludge available for land application application). Biosolids soil amendments are only available at the national scale, and it is not

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[22] A small amount of PRP N (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.

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 amendments 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 propagated through the estimate with replicate sampling weights associated with the survey. N_2O emissions for the PRP manure N deposited on federal grasslands and applied biosolids N are estimated using the Tier 1 method by multiplying the N input by the default emission factor. Emissions from manure N are estimated at the state level and aggregated to the entire country, but emissions from biosolids N 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 2015 based on the Tier 1 and 3 methods, with the exception of biosolids (discussed below). Emissions from 2016 to 2018 are estimated using a splicing method as described in Box 5-4. As with croplands, estimates for 2016 to 2018 will be recalculated in a future Inventory when new NRI data are released by USDA. Biosolids application data are compiled through 2018 in this Inventory, and therefore soil N_2O emissions and confidence intervals are estimated using the Tier 1 method for all years in the time series without application of the splicing method.

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 5-16 and Table 5-17).

Indirect N_2O Emissions Associated with Nitrogen Management in Cropland and Grasslands

Indirect N_2O emissions occur when mineral N 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 N as NO_x and NH_3 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 N incorporated into crops and forage from symbiotic N fixation, and input of N from asymbiotic fixation also contributes to volatilized N emissions. Volatilized N can be returned to soils through atmospheric deposition, and a portion of the deposited N is emitted to the atmosphere as N_2O. The second pathway occurs via leaching and runoff of soil N (primarily in the form of NO_3^-) that is made available through anthropogenic activity on managed lands, mineralization of soil organic matter and residue, including N incorporated into crops and forage from symbiotic N fixation, and inputs of N into the soil from asymbiotic fixation. The NO_3^- 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 N for reporting purposes, which here includes croplands and grasslands.

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

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

The IPCC (2006) default emission factor is multiplied by the volatilization data generated from both DayCent and Tier 1 methods to estimate indirect N_2O emissions occurring due to re-deposition of the volatilized N (see Table 5-19). 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 N, the Tier 3 DayCent model and IPCC (2006) Tier 1 method are combined to estimate the amount of N 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 N 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 N subject to leaching and runoff associated with N applications on croplands that are not simulated by DayCent, biosolids amendments on grasslands, and PRP manure N excreted on federal grasslands.

For both the DayCent Tier 3 and IPCC (2006) Tier 1 methods, nitrate 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 nitrate 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 plus irrigation does not exceed 80 percent of PET.

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 5-19). Further elaboration on the methodology and data used to estimate indirect N_2O emissions are described in Annex 3.12.

Indirect soil N_2O emissions from 2016 to 2018 are estimated using the splicing method that is described in Box 5-4. As with the direct N_2O emissions, the time series will be recalculated in a future Inventory report when new activity data are compiled.

Uncertainty and Time-Series Consistency

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 (N volatilized and leached or runoff) simulated by DayCent; (3) direct emissions calculated with the IPCC (2006) Tier 1 method; (4) the components of indirect emissions (N volatilized and leached or runoff) calculated with the IPCC (2006) Tier 1 method; and (5) indirect emissions estimated with the IPCC (2006) Tier 1 method. Uncertainty in direct emissions, which account for the majority of N_2O emissions from agricultural management, as well as the components of indirect emissions calculated by DayCent are estimated with a Monte Carlo Analysis, addressing uncertainties in model inputs and structure (i.e., algorithms and parameterization) (Del Grosso et al. 2010). For 2016 to 2018, there is additional uncertainty propagated through the Monte Carlo Analysis associated with the splicing method (See Box 5-4).

Simple error propagation methods (IPCC 2006) are used to estimate confidence intervals for direct emissions calculated 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 2016 to 2018 (see Box 5-4). Additional details on the uncertainty methods are provided in Annex 3.12.

Table 5-20 shows the combined uncertainty for direct soil N_2O emissions. The estimated emissions ranges from 31 percent below to 31 percent above the 2018 emission estimate of 285.7 MMT CO_2 Eq. The combined uncertainty for indirect soil N_2O emissions ranges from 69 percent below to 151 percent above the 2018 estimate of 52.5 MMT CO_2 Eq.

Table 5-20: Quantitative Uncertainty Estimates of N_2O Emissions from Agricultural Soil Management in 2018 (MMT CO_2 Eq. and Percent)

Source	Gas	2018 Emission Estimate (MMT CO_2 Eq.)	Uncertainty Range Relative to Emission Estimate (MMT CO_2 Eq.)		Uncertainty Range Relative to Emission Estimate (%)	
			Lower Bound	Upper Bound	Lower Bound	Upper Bound
Direct Soil N_2O Emissions	N_2O	285.7	197.5	373.8	-31%	31%
Indirect Soil N_2O Emissions	N_2O	52.5	16.1	132.0	-69%	151%

Note: Due to lack of data, uncertainties in PRP manure N production, other organic fertilizer amendments, and biosolids (i.e., sewage sludge) amendments to soils are currently treated as certain; these sources of uncertainty will be included in future Inventory reports.

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 mineral fertilizer and PRP N additions in Alaska and Hawaii, and drained organic soils in 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 small for the other sources of N (e.g., crop residue inputs), which are not currently included in the Inventory.

Methodological recalculations were applied to the entire time series to ensure time-series consistency from 1990 through 2018. Details on the emission trends through time are described in more detail in the Methodology section.

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 representing 796 different combinations of fertilizer treatments and cultivation practices, and measurement data for grassland are available for 13 sites representing 36 different management treatments. Nitrate leaching data are available for 12 sites, representing 279 different combinations of fertilizer treatments and tillage practices. 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.

The original statistical model developed from the comparisons to experimental data did not separate freeze-thaw affected areas from areas that are not affected by freeze-thaw cycles. Freeze-thaw cycles lead to hot moments or pulses in emissions that substantially increase annual emissions (Wagner-Riddle et al. 2017). The empirical model estimated that emissions were too high at NRI sites with freeze-thaw effects because most of the experimental sites are not influenced by freeze-thaw events, and this led to a reduction in emissions from freeze-thaw events. Therefore, corrective actions were taken to include a freeze-thaw indicator variable in the statistical model to address differences in the DayCent model prediction capability for experimental sites with and without freeze-thaw events.

In addition, quality control uncovered an error in the DayCent simulations associated with no grazing on pastures and rangelands during the recent historical period from 1980 to 2015. In the initial simulations, this led to a large increase in N additions to soils from crop and grass residues. Corrective actions were taken to ensure grazing was simulated on pastures and rangelands by the DayCent Model.

Spreadsheets containing input data and probability distribution functions required for DayCent simulations of croplands and grasslands and unit conversion factors have been checked, in addition to the program scripts that are used to run the Monte Carlo uncertainty analysis. Links between spreadsheets have also been checked, updated, and corrected when necessary. Spreadsheets containing input data, emission factors, and calculations required for the Tier 1 method have been checked and updated as needed.

Recalculations Discussion

Methodological recalculations are applied to the entire time-series to ensure time-series consistency from 1990 through 2018. Several major improvements have been implemented in this Inventory leading to the need for recalculations, including (1) development of a more detailed time series of management activity data by combining information in an imputation analysis from USDA-NRCS CEAP survey, USDA-ERS ARMS data, CTIC data and USDA Census of Agriculture data; (2) incorporating new land use and crop histories from the NRI survey; (3) incorporating new land use data from the NLCD; (4) modeling SOC stock changes to 30 cm depth with the Tier 3 approach (previously modeled to 20 cm depth), which influences the mineralization of N from soil organic matter decomposition; (5) modeling the N cycle with freeze-thaw effects on soil N_2O emissions; and (6) addressing the effect of cover crops on greenhouse gas emissions and removals. Other improvements include better resolving the timing of tillage, planting, fertilization and harvesting based on the USDA-NRCS CEAP survey and state level information on planting and harvest dates; improving the timing of irrigation; and crop senescence using growing degree relationships. The surrogate data method was also applied to re-estimate N_2O emissions from 2016 to 2017. These changes resulted in an average increase in emissions of 22 percent from 1990 to 2017 relative to the previous Inventory.

Planned Improvements

A key improvement for a future Inventory will be to incorporate additional management activity data from the USDA-NRCS Conservation Effects Assessment Project survey. This survey has compiled new data in recent years that will be available for the Inventory analysis by next year. The latest land use data will also be incorporated from the USDA National Resources Inventory and related management data from USDA-ERS ARMS surveys.

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. Model development is underway to represent the influence of nitrification inhibitors and slow-release fertilizers (e.g., polymer-coated fertilizers) on N_2O emissions. Experimental study sites will continue to be added for quantifying model structural uncertainty. Studies that have continuous (daily) measurements of N_2O (e.g., Scheer et al. 2013) will be given priority.

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). Alaska and Hawaii are not included for all sources in the current Inventory for agricultural soil management, with the exception of N_2O emissions from drained organic soils in croplands and grasslands for Hawaii, synthetic fertilizer and PRP N amendments for grasslands in Alaska and Hawaii. There is also an improvement based on updating the Tier 1 emission factor for N_2O emissions from drained organic soils by using the revised factor in the 2013 Supplement to the *2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands* (IPCC 2013).

In addition, there is a planned improvement associated with implementation of the Tier 1 method. Specifically, soil N_2O emissions will be estimated and reported for N mineralization from soil organic matter decomposition that is accelerated with *Forest Land Converted to Cropland* and *Grassland Converted to Cropland*.

These improvements are expected to be completed for the next full Inventory analysis (i.e., 2022 submission to the UNFCCC, 1990 through 2020 Inventory). However, the timeline may be extended if there are insufficient resources to fund all or part of these planned improvements.

5.5 Liming (CRF 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 liming of soils have fluctuated over the past 25 years in the United States, ranging from 3.1 MMT CO_2 Eq. to 6.0 MMT CO_2 Eq. In 2018, liming of soils in the United States resulted in emissions of 3.1 MMT CO_2 Eq. (0.9 MMT C), representing a 33 percent decrease in emissions since 1990 (see Table 5-21 and Table 5-22). The trend is driven by variation in the amount of limestone and dolomite applied to soils over the time period.

Table 5-21: Emissions from Liming (MMT CO_2 Eq.)

Source	1990	2005	2014	2015	2016	2017	2018
Limestone	4.1	3.9	3.3	3.5	2.8	2.9	3.0
Dolomite	0.6	0.4	0.3	0.3	0.3	0.2	0.2
Total	**4.7**	**4.3**	**3.6**	**3.7**	**3.1**	**3.1**	**3.1**

Note: Totals may not sum due to independent rounding.

Table 5-22: Emissions from Liming (MMT C)

Source	1990	2005	2014	2015	2016	2017	2018
Limestone	1.1	1.1	0.9	0.9	0.8	0.8	0.8
Dolomite	0.2	0.1	0.1	0.1	0.1	0.1	0.1
Total	**1.3**	**1.2**	**1.0**	**1.0**	**0.8**	**0.8**	**0.9**

Note: Totals may not sum due to independent rounding.

Methodology

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 applied (see Table 5-23) were multiplied by CO_2 emission factors from West and McBride (2005). These 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).

The annual application rates of limestone and dolomite were derived from estimates and industry statistics provided in the *Minerals Yearbook* and *Mineral Industry Surveys* (Tepordei 1993 through 2006; Willett 2007a, 2007b, 2009, 2010, 2011a, 2011b, 2013a, 2014, 2015, 2016, 2017, 2018; USGS 2008 through 2018). 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) emission default 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 rives 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 2018 U.S. emission estimate from liming of soils is 3.1 MMT CO_2 Eq. using the U.S.-specific factors. In contrast, emissions would be estimated at 6.4 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 2018 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 2018 data, 2017 fractions were applied to a 2018 estimate of total crushed stone presented in the USGS *Mineral Industry Surveys: Crushed Stone and Sand and Gravel in the First Quarter of 2019* (USGS 2019).

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 5-23: Applied Minerals (MMT)

Mineral	1990		2005		2014	2015	2016	2017	2018
Limestone	19.0		18.1		15.3	16.0	13.0	13.4	13.7
Dolomite	2.4		1.9		1.3	1.2	1.1	0.8	0.8

Uncertainty and Time-Series Consistency

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.

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 5-24. Carbon dioxide emissions from carbonate lime application to soils in 2018 were estimated to be between -0.34 and 5.94 MMT CO_2 Eq. at the 95 percent confidence level. This confidence interval represents a range of 111 percent below to 88 percent above the 2018 emission estimate of 3.1 MMT CO_2 Eq. Note that there is a small probability of a negative emissions value leading to a net uptake of CO_2 from the atmosphere. Net uptake occurs due to the dominance of the carbonate lime dissolving in carbonic acid rather than nitric acid (West and McBride 2005).

Table 5-24: Approach 2 Quantitative Uncertainty Estimates for CO_2 Emissions from Liming (MMT CO_2 Eq. and Percent)

Source	Gas	2018 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	3.1	(0.34)	5.94	-111%	+88%

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

Methodological recalculations were applied to the entire time series to ensure time-series consistency from 1990 through 2018.

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. No errors were found.

Recalculations

Adjustments were made in the current Inventory to improve the results. First, limestone and dolomite application data for 2016 and 2017 were updated with the recently published data from USGS (2019), rather than approximated by a ratio method for 2017. With this revision in the activity data, the emissions decreased by 3.9 and 3.2 percent for 2016 and 2017, respectively, relative to the previous Inventory estimates.

5.6 Urea Fertilization (CRF 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 industrial production process. In the presence of water and urease enzymes, urea 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 totaled 4.6 MMT CO_2 Eq. (1.3 MMT C) in 2018 (Table 5-25 and Table 5-26). Carbon dioxide emissions have increased by 129 percent between 1990 and 2018 due to an increasing amount of urea that is applied to soils. The variation in emissions across the time series is driven by increasing amounts of fertilizer applied to soils.

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

Source	1990		2005		2014	2015	2016	2017	2018
Urea Fertilization	2.0		3.1		3.9	4.1	4.0	4.5	4.6

Table 5-26: CO_2 Emissions from Urea Fertilization (MMT C)

Source	1990		2005		2014	2015	2016	2017	2018
Urea Fertilization	0.5		0.9		1.1	1.1	1.1	1.2	1.3

Methodology

Carbon dioxide emissions from the application of urea to agricultural soils were estimated using the IPCC (2006) Tier 1 methodology. The method assumes that all CO_2 fixed during the industrial process for urea production is released after application. The annual amounts of urea applied to croplands (see Table 5-27) were derived from the state-level fertilizer sales data provided in *Commercial Fertilizer* reports (TVA 1991, 1992, 1993, 1994; AAPFCO 1995 through 2018).[23] These amounts were multiplied by the default IPCC (2006) emission factor (0.20 metric tons of C per metric ton of urea), which is equal to the C content of urea on an atomic weight basis. The calculations were made using a Monte Carlo analysis as described in the Uncertainty section.

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 2016, 2017, and 2018 fertilizer years (i.e., July 2015 through June 2016, July 2016 through June 2017 and July 2017 through June 2018) were not available for this Inventory. Therefore, urea application in the 2016, 2017, and 2018 fertilizer years were estimated using a linear, least squares trend of consumption over the data from the previous five years (2011 through 2015) at the state scale. A trend of five years was chosen as opposed to a longer trend as it best captures the current inter-state and 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 data using the method described above.

Table 5-27: Applied Urea (MMT)

	1990		2005		2014	2015	2016	2017	2018
Urea Fertilizer[a]	3.3		4.8		6.1	6.2	6.5	6.7	6.9

[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 category.

Uncertainty and Time-Series Consistency

An Approach 2 Monte Carlo analysis was conducted as described by the IPCC (2006). The largest source of uncertainty was the default emission factor, which assumes that 100 percent of the C in $CO(NH_2)_2$ applied to soils is ultimately emitted into the environment as CO_2. This factor does not incorporate the possibility that some of the C

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[23] 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.

may be retained in the soil, and therefore the uncertainty range was set from 50 percent emissions to the maximum emission value of 100 percent using a triangular distribution. In addition, urea consumption data also have uncertainty that are represented as normal density distributions. Due to the highly skewed distribution of the emissions from the Monte Carlo analysis, the estimated emissions are based on the mode of the posterior distribution 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 2018 were estimated to be between 2.97 and 5.35 MMT CO_2 Eq. at the 95 percent confidence level. This indicates a range of 35 percent below to 16 percent above the 2018 emission estimate of 4.6 MMT CO_2 Eq. (Table 5-28).

Table 5-28: Quantitative Uncertainty Estimates for CO_2 Emissions from Urea Fertilization (MMT CO_2 Eq. and Percent)

Source	Gas	2018 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	4.6	2.97	5.35	-35%	+16%

[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. Urea for non-fertilizer use, such as aircraft deicing, may be included in consumption totals, but the amount is likely very small. For example, research on aircraft deicing practices based on a 1992 survey found a known annual usage of approximately 2,000 tons of urea for deicing; this would constitute 0.06 percent of the 1992 consumption of urea (EPA 2000). Similarly, surveys conducted from 2002 to 2005 indicate that total urea use for deicing at U.S. airports is estimated to be 3,740 metric tons per year, or less than 0.07 percent of the fertilizer total for 2007 (Itle 2009). In addition, there is uncertainty surrounding the underlying assumptions behind the calculation that converts 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 corresponding increase or decrease in the value for the subsequent year.

Methodological recalculations were applied to the entire time series to ensure time-series consistency from 1990 through 2018. Details on the emission trends through time are described in more detail in the Introduction.

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 errors were found in the calculation. Based on the quality control review, it was not clear if Urea Ammonium Nitrate (UAN) should also be included as a source of CO_2 emissions. This will be further investigated in a future Inventory.

Recalculations

Emissions estimates were derived directly from the Monte Carlo analysis in this Inventory. The mode was selected due to the highly skewed distribution of emissions from the Monte Carlo analysis. The entire time series was recalculated to use the mode of the distribution. This improvement in the calculation of emissions led to estimates that averaged about 13 percent lower than the previous Inventory across the time series.

Planned Improvements

A key planned improvement is to investigate the composition of Urea Ammonium Nitrate (UAN), and determine if UAN should be included in the estimation of Urea CO_2 emissions.

5.7 Field Burning of Agricultural Residues (CRF 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. Field burning of crop residues is not considered a net source of CO_2 emissions because the C released to the atmosphere as CO_2 during burning is reabsorbed during the next growing season by the crop. 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 commonly 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, and wheat (McCarty 2009). In 2018, CH_4 and N_2O emissions from field burning of agricultural residues were 0.4 MMT CO_2 Eq. (16 kt) and 0.2 MMT CO_2 Eq. (0.6 kt), respectively (Table 5-29 and Table 5-30). Annual emissions of CH_4 and N_2O have increased from 1990 to 2018 by 15.7 percent and 15.2 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 of the crop types.

Table 5-29: CH_4 and N_2O Emissions from Field Burning of Agricultural Residues (MMT CO_2 Eq.)

Gas/Crop Type	1990	2005	2014	2015	2016	2017	2018
CH_4	**0.3**	**0.4**	**0.4**	**0.4**	**0.4**	**0.4**	**0.4**
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
Wheat	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Barley	+	+	+	+	+	+	+
Oats	+	+	+	+	+	+	+
Other Small Grains	+	+	+	+	+	+	+
Sorghum	+	+	+	+	+	+	+
Cotton	+	+	+	+	+	+	+
Grass Hay	+	+	+	+	+	+	+
Legume Hay	+	+	+	+	+	+	+
Peas	+	+	+	+	+	+	+
Sunflower	+	+	+	+	+	+	+
Tobacco	+	+	+	+	+	+	+
Vegetables	+	+	+	+	+	+	+
Chickpeas	+	+	+	+	+	+	+
Dry Beans	+	+	+	+	+	+	+
Lentils	+	+	+	+	+	+	+
Peanuts	+	+	+	+	+	+	+
Soybeans	+	+	0.1	+	+	+	+
Potatoes	+	+	+	+	+	+	+
Sugarbeets	+	+	+	+	+	+	+
N_2O	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**
Maize	+	+	0.1	+	+	+	+
Rice	+	+	+	+	+	+	+
Wheat	0.1	0.1	+	0.1	+	+	+

Barley	+	+	+	+	+	+	+
Oats	+	+	+	+	+	+	+
Other Small Grains	+	+	+	+	+	+	+
Sorghum	+	+	+	+	+	+	+
Cotton	+	+	+	+	+	+	+
Grass Hay	+	+	+	+	+	+	+
Legume Hay	+	+	+	+	+	+	+
Peas	+	+	+	+	+	+	+
Sunflower	+	+	+	+	+	+	+
Tobacco	+	+	+	+	+	+	+
Vegetables	+	+	+	+	+	+	+
Chickpeas	+	+	+	+	+	+	+
Dry Beans	+	+	+	+	+	+	+
Lentils	+	+	+	+	+	+	+
Peanuts	+	+	+	+	+	+	+
Soybeans	+	+	+	+	+	+	+
Potatoes	+	+	+	+	+	+	+
Sugarbeets	+	+	+	+	+	+	+
Total	**0.5**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**	**0.6**

+ Does not exceed 0.05 MMT CO_2 Eq.

Note: Totals may not sum due to independent rounding.

Table 5-30: CH_4, N_2O, CO, and NO_x Emissions from Field Burning of Agricultural Residues

Gas/Crop Type	1990	2005	2014	2015	2016	2017	2018
CH_4	**14**	**16**	**16**	**16**	**16**	**16**	**16**
Maize	2	3	5	5	5	5	5
Rice	3	3	3	2	2	2	2
Wheat	5	5	4	5	5	5	5
Barley	+	+	+	+	+	+	+
Oats	+	+	+	+	+	+	+
Other Small Grains	+	+	+	+	+	+	+
Sorghum	+	+	+	+	+	+	+
Cotton	1	2	1	1	1	1	1
Grass Hay	+	+	+	+	+	+	+
Legume Hay	+	+	+	+	+	+	+
Peas	+	+	+	+	+	+	+
Sunflower	+	+	+	+	+	+	+
Tobacco	+	+	+	+	+	+	+
Vegetables	+	+	+	+	+	+	+
Chickpeas	+	+	+	+	+	+	+
Dry Beans	+	+	+	+	+	+	+
Lentils	+	+	+	+	+	+	+
Peanuts	+	+	+	+	+	+	+
Soybeans	1	1	2	2	2	2	2
Potatoes	+	+	+	+	+	+	+
Sugarbeets	+	+	+	+	+	+	+
N_2O	**1**	**1**	**1**	**1**	**1**	**1**	**1**
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	+	+	+	+	+	+	+
CO	**287**	**332**	**338**	**311**	**310**	**308**	**308**
NOx	**12**	**14**	**14**	**13**	**13**	**13**	**13**

+ Does not exceed 0.5 MMT CO_2 Eq.

Note: Totals may not sum due to independent rounding.

Methodology

A U.S.-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 U.S.-specific approach to the IPCC (2006) default approach, see Box 5-6) and a data splicing method with a linear extrapolation was applied to complete the emissions time series from 2015 to 2018. In order to estimate the amounts of C and N released during burning, the following equation is used:

$$\text{C or N released} = \Sigma \text{ for all crop types and states} \left[\frac{\text{AB}}{\text{CAH} \times \text{CP} \times \text{RCR} \times \text{DMF} \times \text{BE} \times \text{CE} \times (\text{FC or FN})} \right]$$

where,

Area Burned (AB) = Total area of crop burned, by state
Crop Area Harvested (CAH) = Total area of crop harvested, by state
Crop Production (CP) = Annual production of crop in kt, by state
Residue: Crop Ratio (RCR) = Amount of residue produced per unit of crop production
Dry Matter Fraction (DMF) = Amount of dry matter per unit of biomass for a crop
Fraction of C or N (FC or FN) = Amount of C or N per unit of dry matter for a crop
Burning Efficiency (BE) = The proportion of prefire fuel biomass consumed[24]
Combustion Efficiency (CE) = The proportion of C or N released with respect to the total amount of C or N available in the burned material, respectively

Crop production data are available by state and year from USDA (2019) for twenty-one crops that are burned in the conterminous United States, including maize, rice, wheat, barley, oats, other small grains, sorghum, cotton,

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[24] In IPCC/UNEP/OECD/IEA (1997), the equation for C or N released contains the variable 'fraction oxidized in burning.' This variable is equivalent to (burning efficiency × combustion efficiency).

grass hay, legume hay, peas, sunflower, tobacco, vegetables, chickpeas, dry beans, lentils, peanuts, soybeans, potatoes, and sugarbeets.[25] Crop area data are based on the 2015 National Resources Inventory (NRI) (USDA-NRCS 2018). In order to estimate total crop production, the crop yield data from USDA Quick Stats crop yields is multiplied by the NRI crop areas. The production data for the crop types are presented in Table 5-31. 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 C or N released through oxidation of the crop residues is used in the following equation to estimate CH_4, CO, N_2O, and NO_x emissions from the Field Burning of Agricultural Residues:

$$\mathrm{CH_4 \text{ and } CO, \text{ or } N_2O \text{ and } NO_x = C \text{ or } N \text{ Released} \times ER \times CF}$$

where,

Emissions Ratio (ER) = 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), or CO-C to C (28/12), or 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 emission rates related to the amount of C and N 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 and factors used in: (1) the current Inventory and (2) the default IPCC (2006) approach was undertaken for the time series from 1990 through 2014 to determine the difference in overall 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:

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

where,

Area Burned (AB) = Total area of crop burned (ha)
Mass Burned ($M_B \times C_f$) = IPCC (2006) default carbon fractions with fuel biomass consumption US-Specific Values using NASS Statistics[26] (metric tons dry matter burnt ha^{-1})
Emission Factor (G_{ef}) = IPCC (2006) emission factor (g kg^{-1} dry matter burnt)

The IPCC (2006) Tier 1 method approach that utilizes default combustion factors and emission factors with mass of fuel values derived from national datasets resulted in 27 percent lower emissions of CH_4 and 49 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 and emissions are estimated based on specific C and N 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

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[25] Sugarcane and 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.

[26] 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.

composition.

Table 5-31: Agricultural Crop Production (kt of Product)

Crop	1990	2005	2013	2014
Maize	296,065	371,256	436,565	453,524
Rice	9,543	11,751	10,894	12,380
Wheat	79,805	68,077	67,388	62,602
Barley	9,281	5,161	4,931	5,020
Oats	5,969	2,646	1,806	2,042
Other Small Grains	2,651	2,051	1,902	2,492
Sorghum	23,687	14,382	18,680	18,436
Cotton	4,605	6,106	3,982	4,396
Grass Hay	44,150	49,880	45,588	46,852
Legume Hay	90,360	91,819	79,669	82,844
Peas	51	660	599	447
Sunflower	1,015	1,448	987	907
Tobacco	1,154	337	481	542
Vegetables	+	1,187	1,844	2,107
Chickpeas	+	5	+	+
Dry Beans	467	1,143	1,110	1,087
Lentils	+	101	72	76
Peanuts	1,856	2,176	2,072	2,735
Soybeans	56,612	86,980	94,756	110,560
Potatoes	18,924	20,026	20,234	19,175
Sugarbeets	24,951	25,635	31,890	31,737

+ Does not exceed 0.5 kt

Note: The amount of crop production has not been analyzed for 2015 to 2018 so a data splicing method is used to estimate emissions for that 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 have been analyzed at 3600 survey locations in the NRI from 1990 to 2002 with LANDFIRE data products developed from 30m Landsat imagery (LANDFIRE 2014), and from 2003 through 2014 using 1km Moderate Resolution Imaging Spectroradiometer imagery (MODIS) Global Fire Location Product (MCD14ML) using combined observations from Terra and Aqua satellites (Giglio et a. 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 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 developed by 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 5-32 shows the resulting percentage of crop residue burned at the national scale by crop type. State-level estimates are also available upon request.

Table 5-32: U.S. Average Percent Crop Area Burned by Crop (Percent)

Crop	1990	2005	2013	2014
Maize	+	+	+	+
Rice	8%	8%	4%	6%
Wheat	1%	2%	2%	1%
Barley	1%	+	1%	1%
Oats	1%	1%	2%	1%
Other Small Grains	1%	1%	1%	1%
Sorghum	1%	1%	1%	1%
Cotton	1%	1%	1%	1%
Grass Hay	+	+	+	+
Legume Hay	+	+	+	+
Peas	+	+	+	+
Sunflower	+	+	+	+
Tobacco	2%	2%	3%	3%
Vegetables	+	+	+	+
Chickpeas	+	1%	+	+
Dry Beans	1%	1%	+	+
Lentils	+	+	+	+
Peanuts	3%	3%	3%	3%
Soybeans	+	+	1%	1%
Potatoes	+	+	+	+
Sugarbeets	+	+	+	+

+ Does not exceed 0.5 percent

Note: The amount of area burned has not been analyzed for 2015 to 2018 so a data splicing method is used to estimate emissions for that portion of the time series.

Additional parameters are needed to estimate the amount of burning, including residue: crop ratios, dry matter fractions, carbon fractions, nitrogen fractions, burning efficiency 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 5-33). The residue C contents for all crops are based on IPCC (2006) default value for herbaceous biomass. The burning efficiency is assumed to be 93 percent, and the combustion efficiency is assumed to be 88 percent, for all crop types (EPA 1994). See Table 5-33 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 5-34).

Table 5-33: Parameters for Estimating Emissions from Field Burning of Agricultural Residues

Crop	Residue/Crop Ratio	Dry Matter Fraction	Carbon Fraction	Nitrogen Fraction	Burning Efficiency (Fraction)	Combustion Efficiency (Fraction)
Maize	0.707	0.56	0.47	0.01	0.93	0.88
Rice	1.340	0.89	0.47	0.01	0.93	0.88
Wheat	1.725	0.89	0.47	0.01	0.93	0.88
Barley	1.181	0.89	0.47	0.01	0.93	0.88
Oats	1.374	0.89	0.47	0.01	0.93	0.88

Other Small Grains	1.777	0.88	0.47	0.01	0.93	0.88
Sorghum	0.780	0.60	0.47	0.01	0.93	0.88
Cotton	7.443	0.93	0.47	0.01	0.93	0.88
Grass Hay	0.208	0.90	0.47	0.02	0.93	0.88
Legume Hay	0.290	0.67	0.47	0.01	0.93	0.88
Peas	1.677	0.91	0.47	0.01	0.93	0.88
Sunflower	1.765	0.88	0.47	0.01	0.93	0.88
Tobacco	0.300	0.87	0.47	0.01	0.93	0.88
Vegetables	0.708	0.08	0.47	0.01	0.93	0.88
Chickpeas	1.588	0.91	0.47	0.01	0.93	0.88
Dry Beans	0.771	0.90	0.47	0.01	0.93	0.88
Lentils	1.837	0.91	0.47	0.02	0.93	0.88
Peanuts	1.600	0.94	0.47	0.02	0.93	0.88
Soybeans	1.500	0.91	0.47	0.01	0.93	0.88
Potatoes	0.379	0.25	0.47	0.02	0.93	0.88
Sugarbeets	0.196	0.22	0.47	0.02	0.93	0.88

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 valuesare 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: combines 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 5-34: 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).

For this Inventory, new activity data on the burned areas have not been analyzed for 2015 to 2018. To complete the emissions time series, a linear extrapolation of the trend is applied to estimate the emissions in the last four years of the inventory. 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 for the last 4 years in the time series from 2015 to 2018 (Brockwell and Davis 2016). The Tier 2 method described previously will be applied to recalculate the emissions for the last 4 years in the time series (2015 to 2018) in a future Inventory.

Uncertainty and Time-Series Consistency

Emissions are estimated using a linear regression model with autoregressive moving-average (ARMA) errors for 2018. The linear regression ARMA model produced estimates of the upper and lower bounds to quantify uncertainty (Table 5-35), and the results are summarized in Table 5-35. Methane emissions from field burning of agricultural residues in 2018 are between 0.33 and 0.46 MMT CO_2 Eq. at a 95 percent confidence level. This indicates a range of 16 percent below and 16 percent above the 2018 emission estimate of 0.4 MMT CO_2 Eq. Nitrous oxide emissions are between 0.14 and 0.20 MMT CO_2 Eq., or approximately 19 percent below and 13 percent above the 2018 emission estimate of 0.2 MMT CO_2 Eq.

Table 5-35: 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	2018 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	0.4	0.33	0.46	-16%	+16%
Field Burning of Agricultural Residues	N_2O	0.2	0.14	0.20	-19%	+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) and sugarcane.

QA/QC and Verification

A source-specific QA/QC plan for field burning of agricultural residues was implemented with Tier 1 analyses, consistent with the U.S. Inventory QA/QC plan outlined in Annex 8. Errors were identified in the assignment of yields to grass hay, legume hay and other close grown crops for calculation of residue burned, and these errors were documented and corrected in the analysis.

Recalculations

Methodological recalculations are associated with two improvements, a) incorporation of new survey data from the USDA National Resources Inventory (USDA-NRCS 2018), and b) a revision to the logistical regression predicting burned area in states that were not directly analyzed for fire occurrence based on remote sensing products (See Methodology section). The logistical regression incorporated revised information on the timing of state legislation to restrict burning of residues in agricultural fields. As a result of these two improvements, the emissions increased on average across the time series by 178 percent and 189 percent for CH_4 and N_2O, respectively. The absolute increases in emissions are 0.2 MMT CO_2 Eq. and 0.1 MMT CO_2 Eq. for CH_4 and N_2O, respectively.

Planned Improvements

The 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 new 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 the DayCent model, and burning events will be simulated directly within the 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 for these sources, and better ensure mass balance of C and N in the Inventory analysis.