

ANNEX 7 Uncertainty – TO BE UPDATED

The annual U.S. Inventory presents the best effort to produce estimates for greenhouse gas source and sink categories in the United States. These estimates were generated according to the UNFCCC reporting guidelines, following the recommendations set forth in the *Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories* (IPCC/UNEP/OECD/IEA 1997), the *IPCC Good Practice Guidance* (IPCC 2000), the Good Practice Guidance for Land Use, Land-Use Change and Forestry (IPCC 2003), and the *2006 Guidelines for National Greenhouse Gas Inventories* (IPCC 2006). This Annex provides an overview of the uncertainty analysis conducted to support the U.S. Inventory, describes the sources of uncertainty characterized throughout the Inventory associated with various source categories (including emissions and sinks), and describes the methods through which uncertainty information was collected, quantified, and presented.

7.1. Overview

The current inventory emission estimates for some source categories, such as for CO₂ Emissions from Fossil Fuel Combustion, have relatively low level of uncertainty associated with them. However, for some other source categories, the inventory emission estimates are considered less certain. The two major types of uncertainty associated with these emission estimates are (1) model uncertainty, which arises when the emission and/or removal estimation models used in developing the inventory estimates do not fully and accurately characterize the respective emission and/or removal processes (due to a lack of technical details or other resources), resulting in the use of incorrect or incomplete estimation methodologies and (2) parameter uncertainty, which arises due to a lack of precise input data such as emission factors and activity data.

The model uncertainty can be partially analyzed by comparing the model results with those of other models developed to characterize the same emission (or removal) process, after taking into account the differences in their conceptual framework, capabilities, data and assumptions. However, it would be very difficult—if not impossible—to quantify the model uncertainty associated with the emission estimates (primarily because, in most cases, only a single model has been developed to estimate emissions from any one source). Therefore, model uncertainty was not quantified in this report. Nonetheless, it has been discussed qualitatively, where appropriate, along with the individual source category description and inventory estimation methodology.

Parameter uncertainty is, therefore, the principal type and source of uncertainty associated with the national inventory emission estimates and is the main focus of the quantitative uncertainty analyses in this report. Parameter uncertainty has been quantified for all of the emission sources and sinks in the U.S. Inventory, with the exception of one very small emission source category, CH₄ emissions from Incineration of Waste, which was included in the 1990-2008 National GHG Inventory for the first time, and two other source categories (International Bunker Fuels and biomass energy consumption) whose emissions are not included in the Inventory totals.

The primary purpose of the uncertainty analysis conducted in support of the U.S. Inventory is (i) to determine the quantitative uncertainty associated with the emission (and removal) estimates presented in the main body of this report [based on the uncertainty associated with the input parameters used in the emission (and removal) estimation methodologies] and (ii) to evaluate the relative importance of the input parameters in contributing to uncertainty in the associated source category inventory estimate and in the overall inventory estimate. Thus, the U.S. Inventory uncertainty analysis provides a strong foundation for developing future improvements and revisions to the Inventory estimation process. For each source category, the analysis highlights opportunities for changes to data measurement, data collection, and calculation methodologies. These are presented in the “Planned Improvements” sections of each source category’s discussion in the main body of the report.

7.2. Methodology and Results

The United States has developed a quality assurance and quality control (QA/QC) and uncertainty management plan (EPA 2002) in accordance with the *IPCC Good Practice Guidance* (IPCC 2000). Like the QA/QC plan, the uncertainty management plan is part of a continually evolving process. The uncertainty management plan provides for a quantitative assessment of the inventory analysis itself, thereby contributing to continuing efforts to understand both what causes uncertainty and how to improve inventory quality. Although the plan provides both general and specific guidelines for implementing quantitative uncertainty analysis, its components are intended to evolve over time, consistent with the

1 inventory estimation process. The U.S. plan includes procedures and guidelines, and forms and templates, for developing
2 quantitative assessments of uncertainty in the national Inventory estimates (EPA 2002).

3 The IPCC *Good Practice Guidance* recommends two approaches—Tier 1 and Tier 2—for developing
4 quantitative estimates of uncertainty in the inventory estimate of individual source categories and the overall inventory. Of
5 these, the Tier 2 approach is both more flexible and reliable than Tier 1; both methods are described in the next section.
6 The United States is in the process of implementing a multi-year strategy to develop quantitative estimates of uncertainty
7 for all source categories using the Tier 2 approach. For the current Inventory, a Tier 2 approach was implemented for all
8 source categories with the exception of Composting and parts of Agricultural Soil Management source categories.

9 The current Inventory reflects significant improvements over the previous publication in the extent to which the
10 Tier 2 approach to uncertainty analysis was adopted. Each of the new Tier 2 analyses reflects additional detail and
11 characterization of input parameters using statistical data collection, expert elicitation methods and more informed
12 judgment. In following the UNFCCC requirement under Article 4.1, emissions from International Bunker Fuels and
13 Indirect Greenhouse Gas Emissions are not included in the total emissions estimated for the U.S. Inventory; therefore, no
14 quantitative uncertainty estimates have been developed for these source categories.¹⁰⁸ Emissions from biomass combustion
15 are accounted for implicitly in the LULUCF chapter through the calculation of changes in carbon stocks. The Energy
16 sector does provide an estimate of CO₂ emissions from bioenergy consumption provided as a memo item for informational
17 purposes in line with the UNFCCC reporting requirements.

18 **Tier 1 and Tier 2 Approach**

19 The Tier 1 method for estimating uncertainty is based on the error propagation equation. This equation combines
20 the uncertainty associated with the activity data and the uncertainty associated with the emission (or the other) factors.
21 The Tier 1 approach is applicable where emissions (or removals) are usually estimated as the product of an activity value
22 and an emission factor or as the sum of individual sub-source category values. Inherent in employing the Tier 1 method
23 are the assumptions that, for each source category, (i) both the activity data and the emission factor values are
24 approximately normally distributed, (ii) the coefficient of variation (i.e., the ratio of the standard deviation to the mean)
25 associated with each input variable is less than 30 percent, and (iii) the input variables within and across (sub-) source
26 categories are not correlated (i.e., value of each variable is independent of the values of other variables).

27 The Tier 2 method is preferred (i) if the uncertainty associated with the input variables is significantly large, (ii)
28 if the distributions underlying the input variables are not normal, (iii) if the estimates of uncertainty associated with the
29 input variables are correlated, and/or (iv) if a sophisticated estimation methodology and/or several input variables are used
30 to characterize the emission (or removal) process correctly. In practice, the Tier 2 is the preferred method of uncertainty
31 analysis for all source categories where sufficient and reliable data are available to characterize the uncertainty of the input
32 variables.

33 The Tier 2 method employs the Monte Carlo Stochastic Simulation technique (also referred to as the Monte
34 Carlo method). Under this method, estimates of emissions (or removals) for a particular source category are generated
35 many times (equal to the number of simulations specified) using an uncertainty model, which is an emission (or removal)
36 estimation equation that imitates or is the same as the inventory estimation model for a particular source category. These
37 estimates are generated using the respective, randomly-selected values for the constituent input variables using
38 commercially available simulation software such as *@RISK* or *Crystal Ball*.

39 **Characterization of Uncertainty in Input Variables**

40 Both Tier 1 and Tier 2 uncertainty analyses require that all the input variables are well-characterized in terms of
41 their Probability Density Functions (PDFs). In the absence of particularly convincing data measurements, sufficient data
42 samples, or expert judgments that determined otherwise, the PDFs incorporated in the current source category uncertainty
43 analyses were limited to normal, lognormal, uniform, triangular, and beta distributions. The choice among these five
44 PDFs depended largely on the observed or measured data and expert judgment.

¹⁰⁸ However, because the input variables that determine the emissions from the Fossil Fuel Combustion and the International Bunker Fuels source categories are correlated, uncertainty associated with the activity variables in the International Bunker Fuels was taken into account in estimating the uncertainty associated with the Fossil Fuel Combustion.

Source Category Inventory Uncertainty Estimates

Discussion surrounding the input parameters and sources of uncertainty for each source category appears in the body of this report. Table A-274 summarizes results based on assessments of source category-level uncertainty. The table presents base year (1990 or 1995) and current year (2010) emissions for each source category. The combined uncertainty (at the 95 percent confidence interval) for each source category is expressed as the percentage deviation above and below the total 2010 emissions estimated for that source category. Source category trend uncertainty is described subsequently in this Appendix.

Table A-274: Summary Results of Source Category Uncertainty Analyses

Source Category	Base Year Emissions ^a	2010 Emissions ^a	2010 Uncertainty ^b	
	Tg CO ₂ Eq.	Tg CO ₂ Eq.	Low	High
CO₂	5,100.1	5,706.0	-2%	4%
Fossil Fuel Combustion ^c	4,737.9	5,387.4	-2%	5%
Non-Energy Use of Fuels	119.6	125.1	-17%	23%
Iron and Steel Production & Metallurgical Coke Production	99.6	54.3	-16%	17%
Natural Gas Systems	37.6	32.3	-19%	30%
Cement Production	33.3	30.5	-13%	14%
Lime Production	11.5	13.2	-8%	9%
Incineration of Waste	8.0	12.1	-21%	24%
Limestone and Dolomite Use	5.1	10.0	-13%	18%
Ammonia Production	13.0	8.7	-10%	25%
Cropland Remaining Cropland	7.1	8.0	-56%	48%
Urea Consumption for Non-Agricultural Purposes	3.8	4.4	-47%	14%
Soda Ash Production and Consumption	4.1	3.7	-7%	7%
Petrochemical Production	3.3	3.3	-26%	29%
Aluminum Production	6.8	3.0	-49%	2%
Carbon Dioxide Consumption	1.4	2.2	-25%	30%
Titanium Dioxide Production	1.2	1.9	-13%	13%
Ferroalloy Production	2.2	1.7	-12%	12%
Zinc Production	0.6	1.2	-17%	19%
Phosphoric Acid Production	1.5	1.0	-18%	18%
Wetlands Remaining Wetlands	1.0	1.0	-33%	38%
Lead Production	0.5	0.5	-15%	15%
Petroleum Systems	0.4	0.3	-24%	149%
Silicon Carbide Production and Consumption	0.4	0.2	-9%	10%
<i>Land Use, Land-Use Change, and Forestry (Sink)^d</i>	<i>(881.8)</i>	<i>(1,074.7)</i>	<i>11%</i>	<i>-11%</i>
<i>Biomass - Wood^f</i>	<i>215.2</i>	<i>191.6</i>	<i>NE</i>	<i>NE</i>
<i>International Bunker Fuels^e</i>	<i>111.8</i>	<i>127.8</i>	<i>NE</i>	<i>NE</i>
<i>Biomass - Ethanol^f</i>	<i>4.2</i>	<i>74.5</i>	<i>NE</i>	<i>NE</i>
CH₄	668.3	666.5	-13%	13%
Natural Gas Systems	189.6	215.4	-19%	30%
Enteric Fermentation	133.8	141.3	-11%	18%
Landfills	147.7	107.8	-52%	44%
Coal Mining	84.1	72.6	-13%	16%
Manure Management	31.7	52.0	-18%	20%
Petroleum Systems	35.2	31.0	-24%	149%
Wastewater Treatment	15.9	16.3	-25%	31%
Rice Cultivation	7.1	8.6	-65%	153%
Stationary Combustion	7.5	6.3	-40%	128%
Abandoned Underground Coal Mines	6.0	5.0	-22%	21%
Forest Land Remaining Forest Land	2.5	4.8	-79%	148%
Mobile Combustion	4.7	1.9	-10%	9%
Composting	0.3	1.6	-50%	50%
Petrochemical Production	0.9	0.9	-29%	30%
Iron and Steel Production & Metallurgical Coke Production	1.0	0.5	-21%	22%
Field Burning of Agricultural Residues	0.2	0.2	-40%	42%

Ferroalloy Production		+	+	-12%	12%
Silicon Carbide Production and Consumption		+	+	-9%	9%
Incineration of Waste		+	+	NE	NE
<i>International Bunker Fuels^e</i>		0.2	0.2	NE	NE
N₂O	316.2	306.2	-14%	41%	
Agricultural Soil Management	200.0	207.8	-21%	57%	
Stationary Combustion	12.3	22.6	-56%	72%	
Mobile Combustion	43.9	20.6	-6%	26%	
Manure Management	14.8	18.3	-16%	24%	
Nitric Acid Production	17.6	16.7	-39%	40%	
Wastewater Treatment	3.5	5.0	-77%	99%	
N ₂ O from Product Uses	4.4	4.4	-8%	8%	
Forest Land Remaining Forest Land	2.1	4.3	-72%	137%	
Adipic Acid Production	15.8	2.8	-9%	9%	
Composting	0.4	1.7	-50%	50%	
Settlements Remaining Settlements	1.0	1.4	-49%	163%	
Incineration of Waste	0.5	0.4	-50%	320%	
Field Burning of Agricultural Residues	0.1	0.1	-29%	31%	
Wetlands Remaining Wetlands	+	+	-74%	42%	
<i>International Bunker Fuels^e</i>		0.2	0.2	NE	NE
HFCs, PFCs, and SF₆	120.6	140.3	-1%	11%	
Substitution of Ozone Depleting Substances ^g	30.8	112.2	-1%	13%	
Electrical Transmission and Distribution	26.7	11.8	-22%	25%	
HCFC-22 Production	36.4	8.1	-7%	10%	
Semiconductor Manufacture	2.9	5.4	-10%	10%	
Aluminum Production	18.4	1.6	-51%	6%	
Magnesium Production and Processing	5.4	1.3	-4%	4%	
Total^h	6,205.3	6,819.1	-2%	5%	
Net Emissions (Sources and Sinks)^h	5,323.4	5,744.4	-3%	6%	

Notes:

Totals may not sum due to independent rounding.

*Base Year is 1990 for all sources except Substitution of Ozone Depleting Substances, for which the United States has chosen 1995.

+ Does not exceed 0.05 Tg CO₂ Eq.

NE: Not Estimated

^a Emission estimates reported in this table correspond to emissions from only those source categories for which quantitative uncertainty was performed for the current inventory. Thus the totals reported for 2010 in this table exclude approximately 2.8 Tg CO₂ Eq. of emissions for which quantitative uncertainty was not assessed. Hence, these emission estimates do not match the final total U.S. greenhouse gas emission estimates presented in this inventory. All uncertainty estimates correspond only to the totals reported in this table.

^b The uncertainty estimates correspond to a 95 percent confidence interval, with the lower bound corresponding to 2.5th percentile and the upper bound corresponding to 97.5th percentile.

^c This source category's inventory estimates exclude CO₂ emissions from geothermal sources, as quantitative uncertainty analysis was not performed for that sub-source category. Hence, for this source category, the emissions reported in this table do not match the emission estimates presented in the Energy chapter of the inventory.

^d Sinks are only included in Net Emissions.

^e Emissions from International Bunker Fuels are not included in the totals.

^f Emissions from Wood Biomass and Ethanol Consumption are not included specifically in summing energy sector totals.

^g This source category's estimate for 2010 excludes 2.4 Tg of CO₂ Eq. from several very small emission sources, as uncertainty associated with those sources was not assessed. Hence, for this source category, the emissions reported in this table do not match the emission estimates presented in the Industrial Processes chapter of the inventory.

^h Totals exclude emissions for which uncertainty was not quantified. The Base Year emissions correspond to 1990 estimates for all source categories, with the exception of Substitution of ODS, for which the estimates correspond to 1995. Similarly, the total for HFCs, PFCs, and SF₆ for the Base Year includes 1995 emission estimates for Substitution of ODS and 1990 emission estimates for all other source categories.

Overall (Aggregate) Inventory Level Uncertainty Estimates

The overall level uncertainty estimate for the U.S. greenhouse gas emissions inventory was developed using the IPCC Tier 2 uncertainty estimation methodology. The uncertainty models of all the emission source categories could not be directly integrated to develop the overall uncertainty estimates due to software constraints in integrating multiple, large uncertainty models. Therefore, an alternative approach was adopted to develop the overall uncertainty estimates. The Monte Carlo simulation output data for each emission source category uncertainty analysis were combined by type of gas and the probability distributions were fitted to the combined simulation output data, where such simulated output data

were available. If such detailed output data were not available for particular emissions sources, individual probability distributions were assigned to those source category emission estimates based on the most detailed data available from the quantitative uncertainty analysis performed.

For the Composting and for parts of Agricultural Soil Management source categories, Tier 1 uncertainty results were used in the overall uncertainty analysis estimation. However, for all other emission sources (excluding international bunker fuels, CO₂ from biomass combustion, and CH₄ from incineration of waste), Tier 2 uncertainty results were used in the overall uncertainty estimation.

The overall uncertainty model results indicate that the 2010 U.S. greenhouse gas emissions are estimated to be within the range of approximately 6,682 to 7,137 Tg CO₂ Eq., reflecting a relative 95 percent confidence interval uncertainty range of -2 percent to 5 percent with respect to the total U.S. greenhouse gas emission estimate of approximately 6,819 Tg CO₂ Eq. The uncertainty interval associated with total CO₂ emissions, which constitute about 84 percent of the total U.S. greenhouse gas emissions in 2010, ranges from -2 percent to 4 percent of total CO₂ emissions estimated. The results indicate that the uncertainty associated with the inventory estimate of the total CH₄ emissions ranges from -13 percent to 13 percent, uncertainty associated with the total inventory N₂O emission estimate ranges from -14 percent to 41 percent, and uncertainty associated with high GWP gas emissions ranges from -1 percent to 11 percent.

A summary of the overall quantitative uncertainty estimates is shown below.

Table A-275. Quantitative Uncertainty Assessment of Overall National Inventory Emissions (Tg CO₂ Eq. and Percent)

Gas	2010 Emission	Uncertainty Range Relative to Emission Estimate ^b				Mean ^c	Standard
	Estimate ^a	Lower Bound ^d		Upper Bound ^d		Deviation ^c	
	(Tg CO ₂ Eq.)	(Tg CO ₂ Eq.)	(Tg CO ₂ Eq.)	(Tg CO ₂ Eq.)	(Tg CO ₂ Eq.)	(Tg CO ₂ Eq.)	
CO ₂	5,706.0	5,570	5,958	-2%	4%	5,763	101
CH ₄ ^e	666.5	578	751	-13%	13%	658	43
N ₂ O ^e	306.2	265	431	-14%	41%	339	43
PFC, HFC & SF ₆ ^e	140.3	138	156	-1%	11%	147	4
Total	6,819.1	6,682	7,137	-2%	5%	6,906	117
Net Emissions (Sources and Sinks)	5,744.4	5,575	6,094	-3%	6%	5,830	133

Notes:

^a Emission estimates reported in this table correspond to emissions from only those source categories for which quantitative uncertainty was performed this year. Thus the totals reported in this table exclude approximately 2.8 Tg CO₂ Eq. of emissions for which quantitative uncertainty was not assessed. Hence, these emission estimates do not match the final total U.S. greenhouse gas emission estimates presented in this Inventory.

^b The lower and upper bounds for emission estimates correspond to a 95 percent confidence interval, with the lower bound corresponding to 2.5th percentile and the upper bound corresponding to 97.5th percentile.

^c Mean value indicates the arithmetic average of the simulated emission estimates; standard deviation indicates the extent of deviation of the simulated values from the mean.

^d The lower and upper bound emission estimates for the sub-source categories do not sum to total emissions because the low and high estimates for total emissions were calculated separately through simulations.

^e The overall uncertainty estimates did not take into account the uncertainty in the GWP values for CH₄, N₂O and high GWP gases used in the inventory emission calculations for 2010.

Trend Uncertainty

In addition to the estimates of uncertainty associated with the current year's emission estimates, this Annex also presents the estimates of trend uncertainty. The *IPCC Good Practice Guidance* defines trend as the difference in emissions between the base year (i.e., 1990) and the current year (i.e., 2010) inventory estimates. However, for purposes of understanding the concept of trend uncertainty, the emission trend is defined in this Inventory as the percentage change in the emissions (or removal) estimated for the current year, relative to the emission (or removal) estimated for the base year. The uncertainty associated with this emission trend is referred to as trend uncertainty.

Under the Tier 1 approach, the trend uncertainty for a source category is estimated using the sensitivity of the calculated difference between the base year and the current year (i.e., 2010) emissions to an incremental (i.e., 1 percent) increase in one or both of these values for that source category. The two sensitivities are expressed as percentages: Type A sensitivity highlights the effect on the difference between the base and the current year emissions caused by a 1 percent change in both, while Type B sensitivity highlights the effect caused by a change to only the current year's emissions.

Both sensitivities are simplifications introduced in order to analyze the correlation between the base and the current year estimates. Once calculated, the two sensitivities are combined using the error propagation equation to estimate the overall trend uncertainty.

Under the Tier 2 approach, the trend uncertainty is estimated using Monte Carlo Stochastic Simulation technique. The trend uncertainty analysis takes into account the fact that the base and the current year estimates often share input variables. For purposes of the current Inventory, a simple approach has been adopted, under which the base year source category emissions (or removals) are assumed to exhibit the same uncertainty characteristics as the current year emissions (or removals). Source category-specific PDFs for base year estimates were developed using current year (i.e.,2010) uncertainty output data. These were adjusted to account for differences in magnitude between the two years' inventory estimates. Then, for each source category, a trend uncertainty estimate was developed using the Monte Carlo method. The overall inventory trend uncertainty estimate was developed by combining all source category-specific trend uncertainty estimates. These trend uncertainty estimates present the range of likely change from base year to 2010, and are shown in Table A- 276.

Table A- 276. Quantitative Assessment of Trend Uncertainty (Tg CO₂ Eq. and Percent)

Gas/Source	Base Year	2010	Emissions	Trend Range ^{a,b}	
	Emissions ^a	Emissions ^a	Trend ^a		
	(Tg CO ₂ Eq.)		(%)	(%)	
				Lower Bound	Upper Bound
CO₂	5,100.1	5,706.0	12%	7%	17%
Fossil Fuel Combustion ^c	4,737.9	5,387.4	14%	8%	19%
Non-Energy Use of Fuels	119.6	125.1	5%	-19%	36%
Iron and Steel Production & Metallurgical Coke Production	99.6	54.3	-46%	-57%	-32%
Natural Gas Systems	37.6	32.3	-14%	-40%	22%
Cement Production	33.3	30.5	-8%	-24%	11%
Incineration of Waste	8.0	12.1	51%	10%	107%
Lime Production	11.5	13.2	14%	1%	29%
Limestone and Dolomite Use	5.1	10	95%	57%	142%
Ammonia Production	13	8.7	-33%	-47%	-16%
Cropland Remaining Cropland	7.1	8.0	14%	-53%	177%
Urea Consumption for Non-Agricultural Purposes	3.8	4.4	15%	-34%	99%
Soda Ash Production and Consumption	4.1	3.7	-10%	-18%	0%
Petrochemical Production	3.3	3.3	1%	-33%	51%
Aluminum Production	6.8	3	-56%	-74%	-27%
Carbon Dioxide Consumption	1.4	2.2	56%	4%	133%
Ferroalloy Production	2.2	1.7	-23%	-35%	-8%
Titanium Dioxide Production	1.2	1.9	57%	31%	88%
Wetlands Remaining Wetlands	1	1	-5%	-43%	58%
Phosphoric Acid Production	1.5	1	-33%	-49%	-14%
Zinc Production	0.6	1.2	85%	44%	139%
Petroleum Systems	0.4	0.3	-14%	-63%	101%
Lead Production	0.5	0.5	5%	-15%	30%
Silicon Carbide Production and Consumption	0.4	0.2	-52%	-58%	-45%
<i>Land Use, Land-Use Change, and Forestry (Sink)^d</i>	<i>(881.8)</i>	<i>(1,074.7)</i>	<i>22%</i>	<i>4%</i>	<i>42%</i>
<i>Biomass – Wood^e</i>	<i>215.2</i>	<i>191.6</i>	<i>-11%</i>	<i>NE</i>	<i>NE</i>
<i>International Bunker Fuels^f</i>	<i>111.8</i>	<i>127.8</i>	<i>14%</i>	<i>NE</i>	<i>NE</i>
<i>Biomass – Ethanol^g</i>	<i>4.2</i>	<i>74.5</i>	<i>1663%</i>	<i>NE</i>	<i>NE</i>
CH₄	668.3	666.5	0%	-14%	27%
Natural Gas Systems	189.6	215.4	14%	-20%	61%
Enteric Fermentation	133.8	141.3	6%	-14%	30%
Landfills	147.7	107.8	-27%	-67%	57%
Coal Mining	84.1	72.6	-14%	-29%	9%
Manure Management	31.7	52.0	64%	25%	114%
Petroleum Systems	35.2	31.0	-12%	131%	1136%
Wastewater Treatment	15.9	16.3	3%	-63%	24%
Rice Cultivation	7.1	8.6	21%	-70%	379%
Stationary Combustion	7.5	6.3	-15%	-70%	138%
Abandoned Underground Coal Mines	6.0	5.0	-18%	-40%	13%
Forest Land Remaining Forest Land	2.5	4.8	92%	-69%	1014%
Composting	0.3	1.6	392%	118%	1023%

Petrochemical Production	0.9	0.9	7%	-31%	64%
Iron and Steel Production & Metallurgical Coke Production	1.0	0.5	-46%	-61%	-26%
Field Burning of Agricultural Residues	0.2	0.2	11%	-40%	107%
Ferroalloy Production	+	+	-31%	-42%	-19%
Silicon Carbide Production and Consumption	+	+	-67%	-71%	-62%
Incineration of Waste	+	+	-23%	NE	NE
<i>International Bunker Fuels^f</i>	0.2	0.2	-5%	NE	NE
N₂O	316.2	306.2	-3%	-31%	34%
Agricultural Soil Management	200.0	207.8	4%	-36%	66%
Stationary Combustion	12.3	22.6	84%	-36%	443%
Mobile Combustion	43.9	20.6	-53%	-62%	-42%
Manure Management	14.8	18.3	24%	-6%	64%
Nitric Acid Production	17.6	16.7	-5%	-48%	72%
Forest Land Remaining Forest Land	2.1	4.3	103%	-56%	841%
Wastewater Treatment	3.5	5.0	46%	-72%	551%
N ₂ O from Product Uses	4.4	4.4	0%	-12%	12%
Adipic Acid Production	15.8	2.8	-82%	-84%	-80%
Composting	0.4	1.7	392%	121%	994%
Settlements Remaining Settlements	1.0	1.4	43%	-55%	364%
Incineration of Waste	0.5	0.4	-23%	-83%	260%
Field Burning of Agricultural Residues	0.1	0.1	21%	-23%	91%
Wetlands Remaining Wetlands	+	+	-5%	-72%	205%
<i>International Bunker Fuels^f</i>	1.1	1.2	12%	NE	NE
HFCs, PFCs, and SF₆^g	120.6	140.3	16%	12%	35%
Substitution of Ozone Depleting Substances ^h	30.8	112.2	265%	232%	302%
Electrical Transmission and Distribution	26.7	11.8	-56%	-68%	-39%
HCFC-22 Production	36.4	8.1	-78%	-80%	-75%
Semiconductor Manufacture	2.9	5.4	85%	60%	112%
Aluminum Production	18.4	1.6	-92%	-95%	-85%
Magnesium Production and Processing	5.4	1.3	-77%	-78%	-75%
Total^h	6,205.3	6,819.1	10%	5%	16%
Net Emission (Sources and Sinks)	5,323.4	5,744.4	8%	2%	16%

Notes:

Totals may not sum due to independent rounding.

*Base Year is 1990 for all sources except Substitution of Ozone Depleting Substances, for which the United States has chosen to use 1995.

+ Does not exceed 0.05 Tg CO₂ Eq.

NE Not Estimated

^a Emission estimates reported in this table correspond to emissions from only those source categories for which quantitative uncertainty was performed for the current inventory. Thus the totals reported in this table for 2010 exclude approximately 2.8 Tg CO₂ Eq. of emissions for which quantitative uncertainty was not assessed. Hence, these emission estimates do not match the final total U.S. greenhouse gas emission estimates presented in this Inventory. Emissions trends and the emission range were calculated based on the emissions estimates reported in this table and, therefore, may differ from the emissions trends reported elsewhere in this Inventory.

^b The trend range represents a 95 percent confidence interval for the emission trend, with the lower bound corresponding to 2.5th percentile value and the upper bound corresponding to 97.5th percentile value.

^c This source category's inventory estimates exclude CO₂ emissions from geothermal sources, as quantitative uncertainty analysis was not performed for that sub-source category. Hence, for this source category, the emissions reported in this table do not match the emission estimates presented in the Energy chapter of the Inventory.

^d Sinks are only included in Net Emissions.

^e Emissions from Wood Biomass and Ethanol Consumption are not included specifically in summing energy sector totals.

^f Emissions from International Bunker Fuels are not included in the emission totals and emission trend estimates.

^g This source category's inventory estimate for 2010 excludes about 2.4 Tg of CO₂ Eq. from several very small emission sources, as uncertainty associated with those sources was not assessed. Hence, for this source category, the emissions reported in this table do not match the emission estimates presented in the Industrial Processes chapter of the Inventory.

^h Totals exclude emissions for which uncertainty was not quantified. The Base Year emissions correspond to 1990 estimates for all source categories, with the exception of Substitution of ODS, for which the estimates correspond to 1995. Similarly, the total for HFCs, PFCs, and SF₆ for the Base Year includes 1995 emission estimates for Substitution of ODS and 1990 emission estimates for all other source categories.

7.3. Planned Improvements

Identifying the sources of uncertainty in the emission and sink estimates of the Inventory and quantifying the magnitude of the associated uncertainty is the crucial first step towards improving those estimates. Quantitative assessment of the parameter uncertainty may also provide information about the relative importance of input parameters (such as activity data and emission factors), based on their relative contribution to the uncertainty within the source category estimates. Such information can be used to prioritize resources with a goal of reducing uncertainty over time within or among inventory source categories and their input parameters. In the current Inventory, potential sources of

1 model uncertainty have been identified for some emission source categories, and uncertainty estimates based on their
2 parameters' uncertainty have been developed for all the emission source categories, with the exception of CH₄ from
3 incineration of waste, which is a minor emission source category newly added to the Inventory starting with the 2008
4 business year, and the international bunker fuels and wood biomass and ethanol combustion source categories, which are
5 not included in the energy sector totals. Emissions from biomass and ethanol combustion however are accounted for
6 implicitly in the LULUCF chapter through the calculation of changes in carbon stocks. The Energy sector does provide an
7 estimate of CO₂ emissions from bioenergy consumption provided as a memo item for informational purposes.

8 Specific areas that require further research include:

- 9 • *Incorporating excluded emission sources.* Quantitative estimates for some of the sources and sinks of
10 greenhouse gas emissions, such as from some land-use activities, industrial processes, and parts of mobile
11 sources, could not be developed at this time either because data are incomplete or because methodologies do not
12 exist for estimating emissions from these source categories. See Annex 5 of this report for a discussion of the
13 sources of greenhouse gas emissions and sinks excluded from this report. In the future, efforts will focus on
14 estimating emissions from excluded emission sources and developing uncertainty estimates for all source
15 categories for which emissions are estimated.
- 16 • *Improving the accuracy of emission factors.* Further research is needed in some cases to improve the accuracy of
17 emission factors used to calculate emissions from a variety of sources. For example, the accuracy of current
18 emission factors applied to CH₄ and N₂O emissions from stationary and mobile combustion are highly uncertain.
- 19 • *Collecting detailed activity data.* Although methodologies exist for estimating emissions for some sources,
20 problems arise in obtaining activity data at a level of detail in which aggregate emission factors can be applied.
21 For example, the ability to estimate emissions of SF₆ from electrical transmission and distribution is limited due
22 to a lack of activity data regarding national SF₆ consumption or average equipment leak rates.

23 In improving the quality of uncertainty estimates the following include areas that deserve further attention:

- 24 • *Refine Source Category and Overall Uncertainty Estimates.* For many individual source categories, further
25 research is needed to more accurately characterize PDFs that surround emissions modeling input variables. This
26 might involve using measured or published statistics or implementing rigorous elicitation protocol to elicit expert
27 judgments, if published or measured data are not available.
- 28 • *Include GWP uncertainty in the estimation of Overall level and trend uncertainty.* The current year's Inventory
29 does not include the uncertainty associated with the GWP values in the estimation of the overall uncertainty for
30 the Inventory. Including this source would contribute to a better characterization of overall uncertainty and help
31 assess the level of attention that this source of uncertainty warrants in the future.
- 32 • *Improve characterization of trend uncertainty associated with base year Inventory estimates.* The
33 characterization of base year uncertainty estimates could be improved, by developing explicit uncertainty models
34 for the base year. This would then improve the analysis of trend uncertainty. However, not all of the simplifying
35 assumptions described in the "Trend Uncertainty" section above may be eliminated through this process due to a
36 lack of availability of more appropriate data.

37 **7.4. Additional Information on Uncertainty Analyses by Source**

38 The quantitative uncertainty estimates associated with each emission and sink source category are reported in
39 each chapter of this Inventory following the discussions of inventory estimates and their estimation methodology. This
40 section provides additional descriptions of the uncertainty analyses performed for some of the sources, including the
41 models and methods used to calculate the emission estimates and the potential sources of uncertainty surrounding them.
42 These sources are organized below in the same order as the sources in each chapter of the main section of this Inventory.
43 To avoid repetition, the following uncertainty analysis discussions of individual source categories do not include
44 descriptions of these source categories. Hence, to better understand the details provided below, refer to the respective
45 chapters and sections in the main section of this Inventory, as needed. All uncertainty estimates are reported relative to the
46 2010 Inventory estimates for the 95 percent confidence interval, unless otherwise specified.

47 **Energy**

48 The uncertainty analysis descriptions in this section correspond to some source categories included in the Energy
49 Chapter of the Inventory.

Mobile Combustion (excluding CO₂)

Mobile combustion emissions of CH₄ and N₂O per vehicle mile traveled vary significantly due to fuel type and composition, technology type, operating speeds and conditions, type of emission control equipment, equipment age, and operating and maintenance practices.

The primary activity data for on-road vehicles, VMT, are collected and analyzed each year by government agencies. To determine the uncertainty associated with the activity data used in the calculations of CH₄ and N₂O emissions, the agencies and the experts that supply the data were contacted. Because few of these sources were able to provide quantitative estimates of uncertainty, expert judgment was used to assess the quantitative uncertainty associated with the activity data.

The estimates of VMT for on-road vehicles by vehicle type in the U.S. were provided by the FHWA (1996 through 2012), and were generated through a cooperative process between the FHWA and the state and the local governments. These estimates are subject to several possible sources of error, such as unregistered vehicles, and measurement and estimation errors. These VMT were apportioned by fuel type, based on data from DOE (1993 through 2011), and then allocated to individual model years using temporal profiles of both the vehicle fleet by age and vehicle usage by model year in the U.S. provided by EPA (2011a) and EPA (2000). While the uncertainty associated with the total national VMT is believed to be low, the uncertainty within individual source categories was considered to be higher due to the uncertainty associated with apportioning total VMT into individual vehicle categories, by fuel type, technology type, and by equipment age. It was assumed that smaller sources had greater percentage uncertainty and vice-versa. Another source of uncertainty in the estimates occurs due to differences in the FHWA and the EPA data sources. For example, the FHWA data are used for defining vehicle types and for developing the estimates of VMT by vehicle type; whereas, the estimates of VMT by fuel types are calculated using EPA's definition of vehicle categories (which differ from those of the FHWA).

The emission factors for on-road vehicles used in the Inventory were obtained from ICF (2006b) and ICF (2004). These factors were based on laboratory testing of vehicles. While the controlled testing environment simulates real driving conditions, emission results from such testing can only approximate real world conditions and emissions. For some vehicle and control technology types, because the testing did not yield statistically significant results within the 95 percent confidence interval, expert judgment was adopted in developing the emission factors. In those cases, the missing emission factors were extrapolated based on the data available on the other emission factors and the emissions factors available for similar vehicle and control technology type. For example, if light duty trucks with an oxidation catalyst has no testing (or not significant testing) results and if light duty cars with an oxidation catalyst had testing results, the CH₄ and the N₂O emission factors for the trucks were calculated from the corresponding emissions factors for the car based upon the ratio of CO₂ emissions per mile for the car to the truck.

A total of 111 highway data input variables were simulated through Monte Carlo Simulation technique using @RISK software. Variables included VMT and emission factors for individual conventional and alternative fuel vehicle categories and technologies. In developing the uncertainty estimation model, a normal distribution was assumed for all but two activity-related input variables (e.g., VMT); in the case of the two input variables, buses and percent of diesel combination trucks, triangular distributions were assumed. The dependencies and other correlations among the activity data were incorporated into the model to ensure consistency in the model specification and simulation. Emission factors were assigned uniform distributions, with the upper and the lower bounds assigned based on 95 percent confidence intervals of laboratory test data. In cases where data did not yield statistically significant results within the 95 percent confidence interval, estimates of upper and lower bounds were determined using expert judgments. For biodiesel vehicles, because no test data were available, consistent with the assumptions underlying the ANL GREET model, their N₂O and CH₄ emissions were assumed to be same as those for diesel vehicles of similar types. For other alternative fuel vehicles (AFVs), uncertainty estimates were developed based on conventional fuel vehicle emission factors and applicable multipliers, as described in the ICF's AFV emission factors memorandum to EPA (ICF 2006a). The results of the quantitative uncertainty analysis are reported as *quantitative uncertainty estimates* following the mobile source category emissions description in the Energy Chapter of this Inventory.

Emissions from non-road vehicles account for 27 percent of CH₄ emissions from mobile sources and 19 percent of N₂O emissions from mobile sources in 2010. A quantitative analysis of uncertainty in the inventory estimates of emissions from non-road vehicles was performed for the first time for the 2009 inventory. Sources of uncertainty for non-road vehicles were investigated by examining the underlying uncertainty of emission factors and fuel consumption data. A non-road uncertainty assessment module was developed independently and integrated with the highway mobile uncertainty model to facilitate a more comprehensive quantitative analysis of uncertainty for all mobile sources.

1 The fuel consumption data for non-road vehicles were obtained from several sources. Estimates of fuel
2 consumption for non-road vehicles (i.e., equipment used for agriculture, construction, lawn and garden, railroad, airport
3 ground support, etc., as well as recreational vehicles) were generated by the EPA's NONROAD model (EPA 2011b). This
4 model estimates fuel consumption based on estimated equipment/vehicle use (in hours) and average fuel consumed per
5 hour of use. Since the fuel estimates are not based upon documented fuel sales or consumption, a fair degree of
6 uncertainty accompanies these estimates. Estimates of distillate fuel sales for ships and boats were obtained from EIA's
7 *Fuel Oil and Kerosene Sales* (EIA 1991 through 2012). These estimates have a moderate level of uncertainty since EIA's
8 estimates are based on survey data and reflect sales to economic sectors, which may include use by both mobile and non-
9 mobile sources within a sector. Domestic consumption of residual fuel by ships and boats is obtained from EIA (2009a).
10 These estimates fluctuate widely from year to year, and are believed to be highly uncertain. In addition, estimates of
11 distillate and residual fuel sales for ships and boats are adjusted for bunker fuel consumption, which introduces an
12 additional (and much higher) level of uncertainty. Jet fuel and aviation gasoline consumption data are obtained from EIA
13 (2012, FAA (2012), FAA (2011), and FAA (2006). Additionally, all jet fuel consumption in the transportation sector is
14 assumed to be consumed by aircraft. Some jet fuel may also be used for other purposes such as blending with diesel fuel
15 or heating oil. In calculating CH₄ emissions from aircraft, an average emission factor is applied to total jet fuel
16 consumption. This average emission factor takes into account the fact that CH₄ emissions occur only during the landing
17 and take-off (LTO) cycles, with no CH₄ being emitted during the cruise cycle. However, a better approach would be to
18 apply emission factors based on the number of LTO cycles.

19 Emission factors for non-road modes were taken from IPCC/UNEP/OECD/IEA (1997) and Browning (2009).
20 These emission factors are based on laboratory test data and expert judgment, and have similar sources of uncertainty as
21 the on-road emission factors for uncontrolled vehicles.

22 A total of 79 non-road data input variables were simulated in the non-road uncertainty assessment module using
23 @RISK software. To determine the uncertainty associated with the non-road fuel consumption data, the agencies and
24 experts that supply the data were contacted. Since few of these sources were able to provide quantitative estimates of
25 uncertainty, expert judgment was used to assess the quantitative uncertainty associated with the fuel consumption data. A
26 normal distribution was assumed for all non-road activity-related input (fuel use) variables, and the activity variables were
27 assumed to be independent of each other. Uncertainty estimates for non-road emissions factors were developed based on
28 laboratory test data and expert judgment. Beta-PERT distributions were assumed for the emissions factor variables, and
29 correlations among the data were incorporated into the model to ensure consistency in model specification.

30 The results of the quantitative uncertainty analysis are reported as *quantitative uncertainty estimates* following
31 the mobile source category emissions description in the Energy Chapter of this Inventory.

32 **Incineration of Waste**

33 The upper and lower bounds of uncertainty in the CO₂ emissions estimate for Incineration of Waste are 24
34 percent and -21 percent respectively, and in the N₂O emission estimates are 320 percent and -50 percent respectively,
35 relative to the respective 2010 emission estimates, at the 95 percent confidence interval. The uncertainties in the waste
36 combustion emission estimates arise from both the assumptions applied to the data and from the quality of the data. Key
37 factors include MSW combustion rate, fraction oxidized, missing data on MSW composition, average carbon content of
38 MSW components, assumptions on the synthetic/biogenic carbon ratio, and combustion conditions affecting N₂O
39 emissions. For more information on emission estimates from MSW combustion, please refer to the Incineration of Waste
40 section of the Energy chapter. The highest levels of uncertainty surround the variables, whose estimates were developed
41 based on assumptions (e.g., percent of clothing and footwear composed of synthetic rubber); the lowest levels of
42 uncertainty surround variables that were determined by quantitative measurements (e.g., combustion efficiency, carbon
43 content of carbon black). Important sources of uncertainty are as follows:

- 44 • *MSW Combustion Rate.* A source of uncertainty affecting both fossil CO₂ and N₂O emissions is the estimate of
45 the MSW combustion rate. The *BioCycle* (Glenn 1999, Goldstein and Matdes 2000, Goldstein and Matdes 2001,
46 Kaufman et al. 2004a, Kaufman et al. 2004b, Simmons et al. 2006, Arsova et al. 2008, van Haaren et al. 2010)
47 estimate of total waste combustion was used for the N₂O and CH₄ emissions estimates, and waste incineration
48 rate, used for the CO₂ emissions estimate are based on a survey of state officials, who use differing definitions of
49 solid waste and who draw from a variety of sources of varying reliability and accuracy. The survey methodology
50 changed significantly in 2003 and thus the results reported for 2002 are not directly comparable to the earlier
51 results (Kaufman et al. 2004a, 2004b), introducing further uncertainty.
52

- 1 • *Fraction Oxidized.* Another source of uncertainty for the CO₂ emissions estimate is fraction oxidized. Municipal
2 waste combustors vary considerably in their efficiency as a function of waste type, moisture content, combustion
3 conditions, and other factors. A value of 98 percent was assumed for this analysis.
- 4
- 5 • *Missing Data on Municipal Solid Waste Composition.* Disposal rates have been interpolated when there is an
6 incomplete interval within a time series. Where data are not available for years at the end of a time series, they
7 are set equal to the most recent years for which estimates are available.
- 8
- 9 • *Average Carbon Contents.* Average carbon contents were applied to the mass of “Other” plastics combusted,
10 synthetic rubber in tires and municipal solid waste, and synthetic fibers. These average values were estimated
11 from the average carbon content of the known products recently produced. The actual carbon content of the
12 combusted waste may differ from this estimate depending on differences in the chemical formulation between
13 the known and unspecified materials, and differences between the composition of the material disposed and that
14 produced. For rubber, this uncertainty ranges from 59 to 91 percent; for plastics, it may be more significant, as
15 their carbon contents range from 38 to 92 percent. However, overall, this is a small source of uncertainty.
- 16
- 17 • *Synthetic/Biogenic Assumptions.* A portion of the fiber and rubber in municipal solid waste is biogenic in origin.
18 Assumptions have been made concerning the allocation between synthetic and biogenic materials based
19 primarily on expert judgment.
- 20
- 21 • *Combustion Conditions Affecting N₂O Emissions.* Because insufficient data exist to provide detailed estimates of
22 N₂O emissions for individual combustion facilities, the estimates presented exhibit high uncertainty. The
23 emission factor for N₂O from municipal solid waste combustion facilities used in the analysis corresponds to the
24 default emission factor for continuously fed stoker units found in IPCC (2006). Using this emission factor
25 assumes that all waste combustors in the United States use continuously fed stoker technology, which is
26 uncertain. Due to a lack of information on the control of N₂O emissions from MSW combustion facilities in the
27 United States, the estimate of zero percent for N₂O emissions control removal efficiency also exhibits
28 uncertainty.

29 Industrial Processes

30 The uncertainty analysis descriptions in this section correspond to some source categories included in the
31 Industrial Processes Chapter of the Inventory.

32 Ammonia Production

33 The uncertainty upper and lower bounds of the emission estimate for Ammonia Production were 25 percent and -
34 10 percent, respectively, at the 95 percent confidence interval. The European Fertilizer Manufacturer’s Association
35 (EFMA) reported an emission factor range of 1.15 to 1.30 ton CO₂/ton NH₃, with 1.2 ton CO₂/ton NH₃ reported as a
36 typical value. The actual emission factor depends upon the amount of air used in the ammonia production process, with
37 1.15 ton CO₂/ton NH₃ being the approximate stoichiometric minimum that is achievable for the conventional reforming
38 process. By using natural gas consumption data for each ammonia plant, more accurate estimates of CO₂ emissions from
39 ammonia production could be calculated. However, these consumption data are often considered confidential. Also,
40 natural gas is consumed at ammonia plants both as a feedstock to the reforming process and for generating process heat
41 and steam. Natural gas consumption data, if available, would need to be divided into feedstock use (non-energy) and
42 process heat and steam (fuel) use, as CO₂ emissions from fuel use and non-energy use are calculated separately.¹⁰⁹

¹⁰⁹ It appears that the IPCC emission factor for ammonia production of 1.5 ton CO₂ per ton ammonia may include both CO₂ emissions from the natural gas feedstock to the process and some CO₂ emissions from the natural gas used to generate process heat and steam for the process. Table 2-5, Ammonia Production Emission Factors, in Volume 3 of the *Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories Reference Manual* (IPCC 1997) includes two emission factors, one reported for Norway and one reported for Canada. The footnotes to the table indicate that the factor for Norway does not include natural gas used as fuel but that it is unclear whether the factor for Canada includes natural gas used as fuel. However, the factors for

1 Natural gas feedstock consumption data for the U.S. ammonia industry as a whole are available from the Energy
2 Information Administration (EIA) *Manufacturers Energy Consumption Survey* (MECS) for the years 1985, 1988, 1991,
3 1994 and 1998 (EIA 1994, 1998). These feedstock consumption data collectively correspond to an effective average
4 emission factor of 1.0 ton CO₂/ton NH₃, which appears to be below the stoichiometric minimum that is achievable for the
5 conventional steam reforming process. The EIA data for natural gas consumption for the years 1994 and 1998 correspond
6 more closely to the CO₂ emissions calculated using the EFMA emission factor than do data for previous years. The 1994
7 and 1998 data alone yield an effective emission factor of 1.1 ton CO₂/ton NH₃, corresponding to CO₂ emission estimates
8 that are approximately 1.5 Tg CO₂ Eq. below the estimates calculated using the EFMA emission factor of 1.2 ton CO₂/ton
9 NH₃. Natural gas feedstock consumption data are not available from EIA for other years, and data for 1991 and previous
10 years may underestimate feedstock natural gas consumption, and therefore the EFMA emission factor was used to estimate
11 CO₂ emissions from ammonia production, rather than EIA data.

12 Research indicates that there is only one U.S. plant that manufactures ammonia from petroleum coke. Carbon
13 dioxide emissions from this plant are explicitly accounted for in the Inventory estimates. No data for ammonia plants
14 using naphtha or other feedstocks other than natural gas have been identified. Therefore, all other CO₂ emissions from
15 ammonia plants are calculated using the emission factor for natural gas feedstock. However, actual emissions may differ
16 because processes other than catalytic steam reformation and feedstocks other than natural gas may have been used for
17 ammonia production. Urea is also used for other purposes than as a nitrogenous fertilizer. Currently, urea used as a
18 nitrogenous fertilizer is accounted for in the LULUCF chapter. Research has identified one ammonia production plant that
19 is recovering byproduct CO₂ for use in EOR. Such CO₂ is currently assumed to remain sequestered (see the section of this
20 chapter on CO₂ Consumption); however, time series data for the amount of CO₂ recovered from this plant are not available
21 and therefore all of the CO₂ produced by this plant is assumed to be emitted to the atmosphere and allocated to Ammonia
22 Manufacture.

23 **Phosphoric Acid Production**

24 The uncertainty upper and lower bounds of the emissions estimate for Phosphoric Acid Production were 18
25 percent and -18 percent, respectively, at the 95 percent confidence interval. Factors such as the composition of phosphate
26 rock affect CO₂ emissions from phosphoric acid production. For more information on how emissions estimates were
27 calculated, please refer to the Phosphoric Acid Production section of the Industrial Processes chapter. Only one set of data
28 from the Florida Institute of Phosphate Research (FIPR) was available for the composition of phosphate rock mined
29 domestically and imported, and data for uncalcined phosphate rock mined in North Carolina and Idaho were unavailable.
30 Inorganic carbon content (as CO₂) of phosphate rock could vary ± 1 percent, resulting in a variation in CO₂ emissions of
31 ± 20 percent.

32 Organic C is not included in the calculation of CO₂ emissions from phosphoric acid production. However, if, for
33 example, 50 percent of the organic carbon content of the phosphate rock were to be emitted as CO₂ in the phosphoric acid
34 production process, the CO₂ emission estimate would increase by approximately 50 percent. If it is assumed that 100
35 percent of the reported domestic production of phosphate rock for Idaho and Utah was first calcined, and it is assumed that
36 50 percent of the organic carbon content of the total production for Idaho and Utah was converted to CO₂ in the
37 calcination process, the CO₂ emission estimate would increase on the order of 10 percent. If it were assumed that there are
38 zero emissions from other uses of phosphate rock, CO₂ emissions would fall 10 percent.

39 **Iron and Steel & Metallurgical Coke Production**

40 The uncertainty upper and lower bounds of the CO₂ emission estimate for Iron and Steel & Metallurgical Coke
41 Production were 17 percent and -16 percent, respectively, at the 95 percent confidence interval. Factors such as the
42 composition of C anodes and the C content of pig iron and crude steel affect CO₂ emissions from Iron and Steel
43 Production. For more information on emission estimates, please refer to the Iron and Steel Production section of the
44 Industrial Processes chapter.

Norway and Canada are nearly identical (1.5 and 1.6 tons CO₂ per ton ammonia, respectively) and it is likely that if one value does not include fuel use, the other value also does not. For the conventional steam reforming process, however, the EFMA reports an emission factor range for feedstock CO₂ of 1.15 to 1.30 ton per ton (with a typical value of 1.2 ton per ton) and an emission factor for fuel CO₂ of 0.5 tons per ton. This corresponds to a total CO₂ emission factor for the ammonia production process, including both feedstock CO₂ and process heat CO₂, of 1.7 ton per ton, which is closer to the emission factors reported in the *IPCC 1996 Reference Guidelines* than to the feedstock-only CO₂ emission factor of 1.2 ton CO₂ per ton ammonia reported by the EFMA. Because it appears that the emission factors cited in the *IPCC Guidelines* may actually include natural gas used as fuel, we use the 1.2 tons/ton emission factor developed by the EFMA.

1 It was also assumed that the C contents of all pig iron and crude steel have carbon contents of 4 percent and 1
2 percent, respectively. The carbon content of pig iron can vary between 3.6 and 4.4 percent, while crude steel can have a
3 carbon content of up to 2 percent, although it is typically less than 1 percent (IPCC 2000).

4 **Aluminum Production**

5 The uncertainty upper and lower bounds of the PFCs emission estimate for Aluminum Production were 6 percent
6 and -51 percent, respectively, at the 95 percent confidence interval. The uncertainties associated with three variables were
7 estimated for each smelter: (1) the estimated quantity of aluminum produced, (2) the anode effect minutes per cell day
8 (which may be reported directly or calculated as the product of anode effect frequency and anode effect duration), and (3)
9 the smelter- or technology-specific slope coefficient (or weight fraction). For more information on the effect of these
10 variables on PFC emissions, please refer the Aluminum Production section of the Industrial Processes chapter. The
11 estimated quantity of aluminum produced is assumed to be characterized by a triangular distribution with a minimum
12 value of zero and a maximum value corresponding to the reported production capacity (USGS 2011); whereas the anode
13 effect and slope coefficient (or weight fraction) are assumed to be characterized by a normal distribution. The uncertainty
14 in aluminum production estimates was assumed to be 1 percent for reported data (IPCC 2006). For reported anode effect
15 frequency and duration data, the uncertainties were assumed to be 2 percent and 5 percent, respectively (Kantamaneni et
16 al. 2001). For calculated smelter-specific CF_4 and C_2F_6 slope coefficients the uncertainties were assumed to be 15 percent
17 (IPCC 2006). For smelters applying technology-specific slope coefficients or weight fractions, the uncertainty in the
18 coefficients was based on the standard deviation of the individual measurements used to determine the average value given
19 by the IPCC guidance for technology-specific (Tier 2) slope coefficients. Consequently, the uncertainty value assigned to
20 the technology-specific slope coefficients for CF_4 for CWPB was 0.036, and for C_2F_6 for CWPB was 0.060. (The
21 uncertainty in the technology-specific CF_4 slope coefficient for CWPB is reported as 6 percent in IPCC (2006), but was
22 increased to 50 percent in this analysis to better account for measurement uncertainty for an individual facility. The
23 uncertainty in PFC emissions for CWPB facilities (the best behaved of the technology types) is about 50 percent for any
24 given facility using the Tier 2 calculation.) In general, where precise quantitative information was not available on the
25 uncertainty of a parameter, an upper-bound value was used.

26 **Magnesium Production**

27 The uncertainty information pertains to the emission estimates presented in the Magnesium Production section of
28 the Industrial Processes chapter. Please refer to that section for more information about this source. The uncertainty upper
29 and lower bounds of the emissions estimate for Magnesium Production were 4 percent and -4 percent, respectively, at the
30 95 percent confidence interval. An uncertainty of 5 percent was assigned to the data reported by each participant in EPA's
31 SF_6 Emission Reduction Partnership for the Magnesium Industry. If Partners did not report emissions data during the
32 current reporting year, SF_6 emissions data were estimated using available emission factor and production information
33 reported in prior years; the extrapolation was based on the average trend for Partners reporting in the current reporting year
34 and the year prior. The uncertainty associated with the SF_6 usage estimate generated from the extrapolated emission factor
35 and production information was determined using a sum of squares method. A 5 percent uncertainty for the year the
36 Partner last reported was assumed and a 30% uncertainty for each subsequent year was assumed. For those industry
37 processes that are not represented in Partnership, such as permanent mold and wrought casting, SF_6 emissions were
38 estimated using production and consumption statistics reported by USGS and estimated process-specific emission factors
39 (see Table 4-73). The uncertainties associated with the emission factors and USGS-reported statistics were assumed to be
40 75 percent and 25 percent, respectively. Emissions associated with sand casting activities not entirely captured by the
41 Partnership utilized a Partner-reported emission factor with an uncertainty of 75 percent. In general, where precise
42 quantitative information was not available on the uncertainty of a parameter, a conservative (upper-bound) value was used.

43 **Electrical Transmission and Distribution**

44 The uncertainty upper and lower bounds of the emissions estimate for Electrical Transmission and Distribution at
45 the 95 percent confidence interval were 25 percent and -22 percent, respectively. Uncertainty associated with emissions of
46 SF_6 from electrical transmission and distribution stem from the following three quantities: (1) emissions from partners, (2)
47 emissions from non-partners, and (3) emissions from manufacturers of electrical equipment. The uncertainty of partner
48 emissions is related to whether the partner emissions are reported or estimated. For reported partner emissions, individual
49 partner submitted SF_6 data was assumed to have an uncertainty of 10 percent. Based on a Monte Carlo analysis, the
50 cumulative uncertainty of the total partner reported data was estimated to be 5.3 percent. For partner-estimated emissions,
51 the uncertainty associated with emissions extrapolated or interpolated from reported emissions data was assumed to be 20
52 percent. There are two sources of uncertainty that contribute to the non-partner emissions uncertainty. The first is the
53 uncertainty in the coefficients of the regression equations used to estimate emissions from non-partners, and the second is
54 the uncertainty in the total transmission miles for non-partners—the independent variable in the regression equation. The
55 uncertainty in the coefficients (as defined by the regression standard error estimate) is estimated to be ± 20 percent for

1 small utilities and ± 64 percent for large utilities, while the uncertainty in the transmission miles is assumed to be ± 10
2 percent. For equipment manufacturers, the quantity of SF₆ charged into equipment by equipment manufacturers is
3 estimated using partner reported new nameplate capacity data and the estimate for the total industry nameplate capacity.
4 The quantity of SF₆ charged into equipment in 2010 is estimated to have an uncertainty of 70.3 percent, and is derived
5 from the uncertainty in partner reported new nameplate capacity (estimated as 5.5.0 percent using error propagation) and
6 the uncertainty in the estimate for U.S. total nameplate capacity (assumed to be 70 percent).

7 A Monte Carlo analysis was applied to estimate the overall uncertainty of the 2010 emission estimate for
8 SF₆ from electrical transmission and distribution. For each defined parameter (i.e., regression coefficient,
9 transmission mileage, partner-reported and partner-estimated SF₆ emissions data for electric power systems; and SF₆
10 emission rate and statistics for manufacturers), random variables were selected from probability density functions,
11 all assumed to have normal distributions about the mean.

12 **Agriculture**

13 The uncertainty analysis descriptions in this section correspond to some source categories included in the
14 Agriculture Chapter of the Inventory.

15 **Manure Management**

16 The uncertainty information below pertains to the emission estimates presented in the Manure Management
17 section of the Agriculture chapter. Please refer to that section for information about various manure management systems
18 and their effect on emissions from this source. The uncertainty upper and lower bounds of the CH₄ emissions estimate for
19 Manure Management were 20 percent and -18 percent, respectively, at the 95 percent confidence interval. The primary
20 factors that contribute to the uncertainty in the emission estimates are a lack of information on the usage of various manure
21 management systems in each regional location and the exact CH₄ generating characteristics of each type of manure
22 management system. Because of significant shifts in the swine and dairy sectors toward larger farms, it is believed that
23 increasing amounts of manure are being managed in liquid manure management systems. The existing estimates reflect
24 these shifts in the weighted MCFs based on 1992, 1997, and 2002 farm-size data. However, the assumption of a direct
25 relationship between farm size and liquid system usage may not apply in all cases and may vary based on geographic
26 location. In addition, the CH₄ generating characteristics of each manure management system type are based on relatively
27 few laboratory and field measurements, and may not match the diversity of conditions under which manure is managed
28 nationally.

29 Previously, IPCC published a default range of MCFs for anaerobic lagoon systems of 0 to 100 percent, reflecting
30 the wide range in performance that may be achieved with these systems (IPCC 2000). There exist relatively few data
31 points on which to determine country-specific MCFs for these systems. In the United States, many livestock waste
32 treatment systems classified as anaerobic lagoons are actually holding ponds that are substantially organically overloaded
33 and therefore not producing CH₄ at the same rate as a properly designed lagoon. In addition, these systems may not be
34 well operated, contributing to higher loading rates when sludge is allowed to enter the treatment portion of the lagoon or
35 the lagoon volume is pumped too low to allow treatment to occur. Rather than setting the MCF for all anaerobic lagoon
36 systems in the United States based on data available from optimized lagoon systems, a MCF methodology utilizing the
37 van't Hoff-Arrhenius equation was developed to more closely match observed system performance and account for the
38 affect of temperature on system performance.

39 The MCF methodology used in the inventory includes a factor to account for management and design practices
40 that result in the loss of VS from the management system. This factor is currently estimated based on data from anaerobic
41 lagoons in temperate climates, and from only three systems. However, this methodology is intended to account for
42 systems across a range of management practices.

43 Uncertainty also exists with the maximum CH₄ producing potential of VS excreted by different animal groups
44 (i.e., B₀). The B₀ values used in the CH₄ calculations are published values for U.S. animal waste. However, there are
45 several studies that provide a range of B₀ values for certain animals, including dairy and swine. The B₀ values chosen for
46 dairy assign separate values for dairy cows and dairy heifers to better represent the feeding regimens of these animal
47 groups. For example, dairy heifers do not receive an abundance of high energy feed and consequently, dairy heifer
48 manure will not produce as much CH₄ as manure from a milking cow. However, the data available for B₀ values are
49 sparse, and do not necessarily reflect the rapid changes that have occurred in this industry with respect to feed regimens.

50 **Rice Cultivation**

51 The uncertainty upper and lower bounds of the emission estimate for Rice Cultivation were 153 percent and -65
52 percent, respectively, at the 95 percent confidence interval. Factors such as primary rice-cropped area, ratooning, and

1 flooding affect greenhouse gas emissions from this source. For more information on emissions estimates for Rice
2 Cultivation, please refer to that section in the Agriculture Chapter. Uncertainty associated with primary rice-cropped area
3 for each state was assumed to range from 1 percent to 5 percent of the mean area based on expert judgment. A normal
4 distribution of uncertainty, truncated to avoid negative values, was assumed about the mean for areas.

5 Ratooned area data are an additional source of uncertainty. Although ratooning accounts for only 5 to 10 percent
6 of the total rice-cropped area, it is responsible for about 15 to 30 percent of total emissions. For states that have never
7 reported any ratooning, it is assumed with complete certainty that no ratooning occurred in 2010. For states that regularly
8 report ratooning, uncertainty is estimated to be between 3 percent and 5 percent (based on expert judgment) and is
9 assumed to have a normal distribution, truncated to avoid negative values. For Arkansas, which reported significant
10 ratooning in 1998 and 1999 only, a triangular distribution was assumed, with a lower boundary of 0 percent ratooning and
11 an upper boundary of 0.034 percent ratooning based on the maximum ratooned area reported in 1998 and 1999.

12 The practice of flooding outside of the normal rice season is also an uncertainty. According to agricultural
13 extension agents, all of the rice-growing states practice this on some part of their rice acreage. Estimates of these areas
14 range from 5 to 68 percent of the rice acreage. Fields are flooded for a variety of reasons: to provide habitat for waterfowl,
15 to provide ponds for crawfish production, and to aid in rice straw decomposition. To date, however, CH₄ flux
16 measurements have not been undertaken over a sufficient geographic range or under a broad enough range of
17 representative conditions to account for this source in the emission estimates or its associated uncertainty.

18 **Agricultural Soil Management**

19 The uncertainty information below pertains to the emission estimates presented in the Agricultural Soil
20 Management section of the Agriculture chapter. Please refer to that section for information about this source. For direct
21 emissions calculated using DAYCENT, uncertainty in the results was attributed to model inputs (i.e., activity data,
22 weather and soil conditions) and the structure of the model (i.e., underlying model equations and parameterization). A
23 Monte Carlo analysis was implemented to address these uncertainties and propagate errors through the modeling process
24 (Del Grosso et al., 2010). The analysis was conducted using probability distribution functions (PDFs) for weather, soil
25 characteristics, and N inputs to simulate direct N₂O emissions for each crop- or grassland type in a county. A joint PDF
26 was used to address the structural uncertainty for direct N₂O emissions from crops, which was derived using an
27 empirically-based method (Ogle et al. 2007). This same Monte Carlo analysis was used to derive uncertainty for the
28 volatilization, runoff, and leaching of N that had been estimated with DAYCENT. County-scale PDFs for weather were
29 based on the variation in temperature and precipitation as represented in DAYMET weather data grid cells (1x1 km)
30 occurring in croplands and grasslands in a county. The National Land Cover Dataset (Vogelman et al. 2001) provided the
31 data on distribution of croplands and grasslands. Similarly, county-scale PDFs for soil characteristics were based on
32 STATSGO Soil Map Units (Soil Survey Staff 2005), that occurred in croplands and grasslands. PDFs for fertilizer were
33 derived from survey data for major U.S. crops, both irrigated and rainfed (ERS 1997; NASS 2004, 1999, 1992; Grant and
34 Krenz 1985). State-level PDFs were developed for each crop if a minimum of 15 data points existed for each of the two
35 categories (irrigated and rainfed). Where data were insufficient at the state-level, PDFs were developed for multi-state
36 Farm Production Regions. Uncertainty in manure application for specific crops was incorporated into the analysis based
37 on total manure available for application in each county, a weighted average application rate, and the crop-specific land
38 area amended with manure for 1997 (compiled from USDA data on animal numbers, manure production, storage
39 practices, application rates and associated land areas receiving manure amendments; see Edmonds et al. 2003). Together
40 with the total area for each crop within a county, the result yielded a probability that a given crop in a specific county
41 would either receive manure or not in the Monte Carlo analysis. A ratio of manure N available for application in each year
42 of the inventory relative to 1997 was used to adjust the amount of area amended with manure, under the assumption that
43 changing the amount of manure N available for application would lead to a proportional change in amended area (see the
44 section on Major Crop Types on Mineral Soils for data sources on manure N availability). If soils were amended with
45 manure, a reduction factor was applied to the N fertilization rate accounting for the interaction between fertilization and
46 manure N amendments (i.e., producers reduce mineral fertilization rates if applying manure). Reduction factors were
47 randomly selected from probability distribution factors based on relationships between manure N application and fertilizer
48 rates from USDA cropping survey data (ERS 1997).

49 An empirically-based uncertainty estimator was developed to assess the uncertainty in model structure associated
50 with its' algorithms and parameterization, using a method described by Ogle et al. (2007). This estimator was based on a
51 linear mixed-effect modeling analysis comparing N₂O emission estimates from eight agricultural experiments with 50
52 treatments. Although the dataset was relatively small, modeled emissions were significantly related to measurements with
53 a p-value of less than 0.01. Random effects were included to capture the dependence in time series and data collected
54 from the same experimental site, which were needed to estimate appropriate standard deviations for parameter
55 coefficients. The model structural uncertainty estimator, accounted for bias and prediction error in the DAYCENT model

1 results, as well as random error associated with fine-scale emission predictions in counties over a time series from 1990 to
2 2010. Note that the current application only addresses structural uncertainty in cropland estimates; further development
3 will be needed to address this uncertainty in model estimates for grasslands, which is a planned improvement as more soil
4 N₂O measurement data become available for grassland sites. In general, DAYCENT tended to underestimate emissions if
5 the rates were above 6 g N₂O/ha/day (Del Grosso et al., 2010). Model structural uncertainty was not assessed for N
6 volatilization and leaching/runoff, because sufficient data from field experiments were not available.

7 A simple error propagation method (IPCC 2006) was used to estimate uncertainties for direct emissions
8 estimated with Tier 1 methods, including management of non-major crops (mineral fertilization, crop residues, organic
9 fertilizers) and N inputs that were not addressed in the DAYCENT simulations (i.e., sewage sludge N, PRP manure N
10 excreted on federal grasslands). Similarly, indirect emissions from N inputs that were not simulated with DAYCENT
11 were calculated according to the IPCC methodology using the simple error propagation method (IPCC 2006). PDFs for
12 the proportion of N subject to volatilization, leaching and runoff, as well as indirect N₂O emission factors were based on
13 IPCC (2006), and PDFs for the activity data were based on the uncertainties associated underlying survey information and
14 calculations.¹¹⁰ For lands simulated by DAYCENT, uncertainty in indirect emissions was derived using the simple error
15 propagation approach, combining uncertainty from the DAYCENT outputs for N volatilization and leaching/runoff with
16 uncertainty in the indirect N₂O emission factors (IPCC 2006).

7 **Field Burning of Agricultural Residues**

18 The uncertainty upper and lower bounds of the CH₄ emission estimate for Field Burning of Agricultural Residues
19 were 42 percent and -40 percent, respectively, and of the N₂O emissions estimate were 31 percent and -29 percent
20 respectively, at the 95 percent confidence interval. Variables such as crop production, residue/crop product ratios, and
21 burning and combustion efficiencies affect greenhouse gas emission estimates for Field Burning of Agricultural Residues.
22 For more information on emission estimates, please refer to the Field Burning of Agricultural Residues section of the
23 Agriculture Chapter. The uncertainty in production for all crops considered here is estimated to be 5 percent, based on
24 expert judgment. The uncertainty in area burned was 7 percent, based on McCarty (2009). Residue/crop product ratios
25 can vary among cultivars. Generic residue/crop product ratios, rather than ratios specific to the United States, have been
26 used for all crops except sugarcane. An uncertainty of 10 percent was applied to the residue/crop product ratios for all
27 crops except for cotton, which was 55 percent. Based on the range given for measurements of soybean dry matter fraction
28 (Strehler and Stützel 1987), residue dry matter contents were assigned an uncertainty of 3.1 percent for all crop types,
29 except for cotton and lentils, which were 10 and 4.4 percent, respectively. Burning and combustion efficiencies were
30 assigned an uncertainty of 5 percent based on expert judgment. The N₂O emission ratio was estimated to have an
31 uncertainty of 28.6 percent based on the range reported in IPCC/UNEP/OECD/IEA (1997). The uncertainty estimated for
32 the CH₄ emission ratio was 40 percent based on the range of ratios reported in IPCC/UNEP/OECD/IEA (1997).

33 **Land Use, Land-Use Change, and Forestry**

34 **Forest Land Remaining Forest Land**

35 ***Changes in Forest Carbon Stocks***

36 Forest area data from the USDA Forest Service and C density data affect total net flux of forest C estimates. For
37 more information on net forest C flux, please refer to the Changes in Forest Carbon Stocks section of the Land Use, Land-
38 Use Change, and Forestry (LULUCF) chapter. The USDA Forest Service inventories are designed to be accurate within 3
39 percent at the 67 percent confidence level (one standard error) per 405,000 ha (1 million acres) of timberland (USDA
40 Forest Service 2006c). For larger areas, the uncertainty in area is concomitantly less, and precision at plot levels is greater.
41 An analysis of uncertainty in growing stock volume data for timber producing land in the Southeast by Phillips et al.
42 (2000) found that nearly all of the uncertainty in their analysis was due to sampling rather than the regression equations
43 used to estimate volume from tree height and diameter. The quantitative uncertainty analysis summarized here primarily
44 focuses on uncertainties associated with the estimates of specific C stocks at the plot level and does not address error in
45 tree diameters or volumes.

46 Estimates for stand-level C pools are derived from extrapolations of site-specific studies to all forest land,
47 because survey data on these pools are not generally available. Such extrapolation introduces uncertainty because
48 available studies may not adequately represent regional or national averages. Uncertainty may also arise due to: (1)
49 modeling errors (e.g., relying on coefficients or relationships that are not well known); and (2) errors in converting

¹¹⁰ With the exception of organic fertilizers and crop yields, which were assumed to have a default ±50 percent uncertainty.

1 estimates from one reporting unit to another (Birdsey and Heath 1995). An important source of uncertainty is that there is
2 little consensus from available data sets on the effect of land-use change and forest management activities (such as
3 harvest) on soil C stocks. For example, while Johnson and Curtis (2001) found little or no net change in soil C following
4 harvest, on average, across a number of studies, many of the individual studies did show differences. Heath and Smith
5 (2000) noted that the experimental design in a number of soil studies limited their usefulness for determining effects of
6 harvesting on soil C. Because soil C stocks are large, estimates need to be very precise, since even small relative changes
7 in soil C sum to large differences when integrated over large areas. The soil C stock and stock change estimates presented
8 here are based on the assumption that soil C density for each broad forest type group stays constant over time. The state of
9 information and modeling are improving in this regard (Woodbury et al. 2006, 2007); the effects of land use and of
10 changes in land use and forest management will be better accounted for in future estimates of soil C.

11 Uncertainty in estimates about the HWP Contribution is based on Monte Carlo simulation of the production
12 approach. The uncertainty analysis is based on Skog et al. (2004), with later revisions made in conjunction with overall
13 revisions in the HWP model (Skog in preparation). The uncertainty analysis for HWP includes an evaluation of the effect
14 of uncertainty in 13 sources including production and trade data, factors to convert products to quantities of C, rates at
15 which wood and paper are discarded, and rates and limits for decay of wood and paper in SWDS.

16 **Direct N₂O fluxes from Forest Soils**

17 The uncertainty upper and lower bounds of the emissions estimate for Direct N₂O Fluxes from Forest Soils were
18 211 percent and -59 percent, respectively, at the 95 percent confidence interval. Variables such as the emission factor for
19 synthetic fertilizer applied to soil, and the area of forest land receiving fertilizer affect Direct N₂O fluxes from Forest Soils.
20 For more information, please refer to that section of the LULUCF chapter. The uncertainty range of the IPCC (2006)
21 default emission factor for synthetic fertilizer applied to soil, ranges from 0.3 to 3 percent. Because IPCC does not
22 provide further information on whether this range represents the 95 percent confidence interval or the absolute minimum
23 and maximum values, a triangular distribution was used to represent the uncertainty of the emission factor. The
24 uncertainty in the area of forest land receiving fertilizer was conservatively estimated at ±20 percent and in fertilization
25 rates at ±50 percent (Binkley 2004).

26 **Cropland Remaining Cropland**

27 The uncertainty information below pertains to the emission estimates presented in the Cropland Remaining
28 Cropland section of the LULUCF chapter. Please refer to that section for information about this source. The uncertainty
29 upper and lower bounds of the emissions estimate for Cropland Remaining Cropland were -172 percent and 167 percent,
30 respectively, at the 95 percent confidence interval. Probability Distribution Functions (PDFs) for fertilizer were based on
31 survey data for major U.S. crops, both irrigated and rainfed (ERS 1997; NASS 2004, 1999, 1992; Grant and Krenz 1985).
32 State-level PDFs were developed for each crop if a minimum of 15 data points existed for each of the two categories
33 (irrigated and rainfed). Where data were insufficient at the state-level, PDFs were developed for multi-state Farm
34 Production Regions. Uncertainty in manure applications for specific crops was incorporated in the analysis based on total
35 manure available for use in each county, a weighted average application rate, and the crop-specific land area amended with
36 manure (compiled from USDA data on animal numbers, manure production, storage practices, application rates and
37 associated land areas receiving manure amendments; see Edmonds et al. 2003). Together with the total area for each crop
38 within a county, this yielded a probability that a given crop at a specific NRI point would either receive manure or not. A
39 ratio of managed manure N production in each year of the inventory relative to 1997 was used to adjust the probability of
40 an area receiving an amendment, under the assumption that greater or less managed manure N production would lead to a
41 proportional change in amended area (see Tier 3 Methods Section for data sources on manure N production). Manure
42 amendment areas were averaged across decades to produce the PDF for the Monte Carlo Analysis (i.e., 1980-1989, 1990-
43 2000). If soils were amended with manure, a reduction factor was applied to the N fertilization rate accounting for the
44 interaction between fertilization and manure N amendments (i.e., producers often reduce mineral fertilization rates if
45 applying manure). Reduction factors were randomly selected from probability distribution factors based on relationships
46 between manure N application and fertilizer rates (ERS 1997). For tillage uncertainty, transition matrices were
47 constructed from CTIC data to represent tillage changes for two time periods, combining the first two and the second two
48 management blocks (i.e., 1980-1989, 1990-2000). A Monte Carlo analysis was conducted with 100 iterations in which
49 inputs values were randomly drawn from the PDFs to simulate the soil C stocks for each NRI cluster of points (i.e.,
50 inventory points in the same county were grouped into clusters if they had the same land-use/management history and soil
51 type) using the Century model.

52 An empirically-based uncertainty estimator was developed to assess uncertainty in model structure associated
53 with the algorithms and parameterization. The estimator was based on a linear mixed effect modeling analysis comparing
54 modeled soil C stocks with field measurements from 45 long-term agricultural experiments with over 800 treatments,
55 representing a variety of tillage, cropping, and fertilizer management practices (Ogle et al. 2006b). The final model

1 included variables for organic matter amendments, N fertilizer rates, inclusion of hay/pasture in cropping rotations, use of
2 no-till, setting-aside cropland from production and inclusion of bare fallow in the rotation. Each of these variables were
3 found to be significant at a 95 percent probability level, and accounted for statistically significant biases in the modeled
4 estimates from Century. For example, Century tended to under-estimate the influence of organic amendments on soil C
5 storage, so a variable was added to adjust the estimate from Century. Random effects captured the dependence in time
6 series and data collected from the same long-term experimental site, which were needed to estimate appropriate standard
7 deviations for parameter coefficients. For each C stock estimate from the Monte Carlo analysis, the structural uncertainty
8 estimator was applied to adjust the value accounting for bias and prediction error in the modeled values. The structural
9 uncertainty estimator was applied by randomly drawing parameter coefficients from their joint probability distribution, in
10 addition to random draws from PDFs representing the uncertainty due to site and site by year random effects. Finally,
11 uncertainty in the land-use and management statistics from the NRI were incorporated into the analysis based on the
12 sampling variance for the clusters of NRI points.

13 The NRI has a two-stage sampling design that allowed PDFs to be constructed assuming a multivariate normal
14 distribution accounting for dependencies in activity data. PDFs for the tillage activity data, as provided by the CTIC, were
15 constructed on a bivariate normal distribution with a log-ratio scale, accounting for the negative dependence among the
16 proportions of land under conventional and conservation tillage practices. PDFs for the agricultural areas receiving
17 manure were derived assuming a normal distribution from county-scale area amendment estimates derived from the
18 USDA Census of Agriculture (Edmonds et al. 2003). Lastly, enrollment in wetland restoration programs was estimated
19 from contract agreements, but due to a lack of information on the margin of error, PDFs were constructed assuming a
20 nominal ± 50 percent uncertainty range.

21 **Mineral Soil Carbon Stock Changes**

22 *Tier 3 Approach*

23 The uncertainty information below pertains to the emission estimates presented in the Mineral Soil Carbon Stock
24 Changes section of the LULUCF chapter. Please refer to that section for information about this source. The uncertainty
25 analysis for the Tier 3 Century inventory had three components: 1) a Monte Carlo approach to address uncertainties in
26 model inputs, 2) an empirically-based approach for quantifying uncertainty inherent in the structure of the Century model,
27 and 3) scaling uncertainty associated with the NRI survey (i.e., scaling from the individual NRI points to the entire U.S.
28 agricultural land base using the expansion factors).

29 For the model input uncertainty, probability distribution functions (PDFs) were developed for fertilizer rates,
30 manure application and tillage practices. An empirically-based uncertainty estimator was developed to assess uncertainty
31 in model structure associated with the algorithms and parameterization. The estimator was based on a linear mixed effect
32 modeling analysis comparing modeled soil C stocks with field measurements from 45 long-term agricultural experiments
33 with over 800 treatments, representing a variety of tillage, cropping, and fertilizer management practices (Ogle et al.
34 2007). The final model included variables for organic matter amendments, N fertilizer rates, inclusion of hay/pasture in
35 cropping rotations, use of no-till, setting-aside cropland from production, and inclusion of bare fallow in the rotation.
36 Each of these variables were found to be significant at a 0.05 alpha level, and accounted for statistically significant biases
37 in modeled estimates from the Century model. Uncertainty in land-use and management statistics from the NRI were
38 incorporated into the analysis based on the sampling variance for the clusters of NRI points.

39 *Tier 2 Approach*

40 For the Tier 2 IPCC method, a Monte Carlo approach was used (Ogle et al. 2003). PDFs for stock change factors
41 were derived from a synthesis of 91 published studies, which addressed the impact of management on SOC storage.
42 Uncertainties in land-use and management activity data were also derived from a statistical analysis.

43 *Additional Mineral C Stock Change Calculations*

44 A ± 50 percent uncertainty was assumed for additional adjustments to the mineral soil C stocks between 1990 and
45 2006; accounting for additional C stock changes associated gains or losses in C sequestration after 1997 due to changes in
46 Conservation Reserve Program enrollment.

47 **Organic Soil Carbon Stock Changes**

48 Uncertainty in C emissions from organic soils was estimated in the same manner described for mineral soil using
49 the Tier 2 method and Monte Carlo analysis. PDFs for emission factors were derived from a synthesis of 10 studies, and
50 combined with uncertainties in the NRI land use and management data for organic soils in the Monte Carlo analysis.
51 Please refer to the Organic Soil C Stock Changes section of the LULUCF chapter for more information on C emissions
52 from organic soils.

CO₂ Emissions from Liming

The uncertainty information below pertains to the emission estimates presented in the Mineral Soil Carbon Stock Changes section of the LULUCF chapter. Please refer to that section for information about liming activity data and the emission factors used for this source. A Monte Carlo (Tier 2) uncertainty analysis was applied to estimate the uncertainty of CO₂ emissions from liming. Uncertainties in the estimates of emissions from liming result from both the emission factors and the activity data. The emission factors used for limestone and dolomite take into account the fate of C following application to soils, including: dissolution of liming constituents; leaching of bicarbonates into the soil and transport to the ocean; and emissions to the atmosphere (West and McBride 2005). The C accounting behind these emission factors entails assumptions about several uncertain factors. First, it is uncertain what fraction of agricultural lime is dissolved by nitric acid (HNO₃)—a process that releases CO₂—and what portion reacts with carbonic acid (H₂CO₃), resulting in the uptake of CO₂. The fractions can vary depending on soil pH and N fertilizer use. The second major source of uncertainty is the fraction of bicarbonate (HCO₃⁻) that leaches through the soil profile and is transported into groundwater, which can eventually be transferred into rivers and into the ocean. This fraction can vary depending on the soil pH and whether calcium (Ca²⁺) and magnesium (Mg²⁺) liming constituents that might otherwise accompany HCO₃⁻, are taken up by crops, remain in the upper soil profile, or are transported through or out of the soil profile. Finally, the emission factors do not account for the time that is needed for leaching and transport processes to occur.

There are several sources of uncertainty in the limestone and dolomite activity data. When reporting data to the USGS (or U.S. Bureau of Mines), some producers do not distinguish between limestone and dolomite. In these cases, data are reported as limestone, so this reporting could lead to an overestimation of limestone and an underestimation of dolomite. In addition, the total quantity of crushed stone listed each year in the *Minerals Yearbook* excludes American Samoa, Guam, Puerto Rico, and the U.S. Virgin Islands.

Land Converted to Cropland

Tier 2 Approach

The uncertainty upper and lower bounds of the emissions estimate for Land Converted to Cropland were 36 percent and -40 percent, respectively, at the 95 percent confidence interval. The uncertainty analysis for *Land Converted to Cropland* using the Tier 2 approach was based on the same method described for *Cropland Remaining Cropland*.

Mineral and Organic Soil Carbon Stock Changes

The quantitative estimates of uncertainty presented above are missing several components. This section qualitatively describes these contributors to overall uncertainty. The agricultural soil C inventory has undergone several improvements during the past few years, such as the development of the Tier 3 inventory method to estimate mineral soil C stock changes for the majority of U.S. cropland. However, some limitations remain in the analysis. First, the current agricultural soil C inventory includes some points designated as non-agricultural land-uses in the NRI if the points were categorized as cropland in either 1992 or 1997, but were urban, water, or miscellaneous non-cropland (e.g., roads and barren areas) in another year. The impact on soil organic C (SOC) storage that results from converting non-agricultural uses to cropland is not well-understood, and therefore, those points were not included in the calculations for mineral soils (emissions from organic soils, however, were computed for those points in the years that they were designated as an agricultural use). Similarly, the effect of aquaculture (e.g., rice cultivation followed by crayfish production in flooded fields) on soil C stocks has not been estimated due to a lack of experimental data. Second, the current estimates may underestimate losses of C from organic soils because the *1997 National Resources Inventory* was not designed as a soil survey and organic soils frequently occur as relatively small inclusions within major soil types. Lastly, the IPCC Tier 2 methodology does not take into account changes in SOC stocks due to pre-1982 land use and land-use change.

Grassland Remaining Grassland

Tier 2 Approach

The uncertainty upper and lower bounds of the emissions estimate for Grassland Remaining Grassland were -32 percent and 25 percent, respectively, at the 95 percent confidence interval. The uncertainty analysis for *Grassland Remaining Grassland* using the Tier 2 approach was based on the same method described for *Cropland Remaining Cropland*.

Additional Uncertainties in Mineral and Organic Soil C Stock Changes

The quantitative estimates of uncertainty presented above are missing several components. This section qualitatively describes these contributors to overall uncertainty. Minimal data exist on where and how much sewage sludge has been applied to U.S. agricultural land and the accounting of this activity appears to be much more difficult than the related-activity of using manure to amend agricultural soils. Consequently, there is considerable uncertainty in the

1 application of sewage sludge, which is assumed to be applied to *Grassland Remaining Grassland*. However, some sludge
2 may be applied to other agricultural land, but there is not sufficient information to further subdivide application among the
3 agricultural land use/land-use change categories. Another limitation is that the current estimates may underestimate losses
4 of C from organic soils because the *1997 National Resources Inventory* was not designed as a soil survey and organic soils
5 frequently occur as relatively small inclusions within major soil types. Lastly, the IPCC Tier 2 methodology does not take
6 into account changes in SOC stocks due to pre-1982 land use and land-use change.

7 **Land Converted to Grassland**

8 **Tier 2 Approach**

9 The uncertainty upper and lower bounds of the emissions estimate for Land Converted to Grassland were -15
10 percent and 15 percent, respectively, at the 95 percent confidence interval. The uncertainty analysis for *Land Converted to*
11 *Grassland* using the Tier 2 approach was based on the same method described for *Cropland Remaining Cropland*. See the
12 Tier 2 section under mineral soils in the *Cropland Remaining Cropland* section for additional discussion.

13 **Additional Uncertainties in Mineral and Organic Soil Carbon Stock Changes**

14 The quantitative estimates of uncertainty presented above are missing several components. This section
15 qualitatively describes these contributors to overall uncertainty. The agricultural soil C inventory has undergone several
16 improvements during the past few years, such as the development of the Tier 3 inventory method to estimate mineral soil
17 C stock changes for the majority of U.S. grassland. However, some limitations remain in the analysis. First, the current
18 agricultural soil C inventory includes some points designated as non-agricultural land-uses in the NRI if the points were
19 categorized as agricultural land use in either 1992 or 1997, but were urban, water, or miscellaneous non-cropland (e.g.,
20 roads and barren areas) in another year. The impact on SOC storage that results from converting non-agricultural uses to
21 grassland is not well-understood, and therefore, those points were not included in the calculations for mineral soils
22 (emissions from organic soils, however, were computed for those points in the years that they were designated as
23 grassland). Second, the current estimates may underestimate losses of C from organic soils because the *1997 National*
24 *Resources Inventory* was not designed as a soil survey and organic soils frequently occur as relatively small inclusions
25 within major soil types. Lastly, this IPCC Tier 2 methodology does not take into account changes in SOC stocks due to
26 pre-1982 land use and land-use change.

27 **Settlements Remaining Settlements**

28 **N₂O Fluxes from Settlement Soil**

29 The uncertainty information below pertains to the emission estimates presented in the N₂O Fluxes from
30 Settlement Soils section of the LULUCF chapter. Please refer to that section for information about synthetic fertilizer N,
31 the amounts of sewage sludge applied to non-agricultural lands, and other variables that affect this source. The uncertainty
32 upper and lower bounds of the emissions estimate for N₂O fluxes from Settlement Soil were 163 percent and -49 percent,
33 respectively, at the 95 percent confidence interval. The uncertainty range for the IPCC's default emission factor for
34 mineral and organic N additions applied to soil ranges from 0.3 to 3 percent (IPCC 2006). Because the IPCC does not
35 provide further information on whether this range represents the 95 percent confidence interval or the absolute minimum
36 and maximum values, a triangular distribution was used to represent the uncertainty of the emission factor.

37 The uncertainty in the total amount of synthetic fertilizer N applied in the United States was estimated to be ±3
38 percent (Terry 2005). The uncertainty in the amount of synthetic fertilizer N applied to settlement soils was
39 conservatively estimated to be ±50 percent, since no uncertainty was provided in Ruddy et al. (2006). The uncertainty in
40 the amounts of sewage sludge applied to non-agricultural lands and used in surface disposal was based on the uncertainty
41 of the following data points: (1) N content of sewage sludge; (2) total sludge applied in 2000; (3) wastewater existing
42 flow in 1996, 2000, and 2004; and (4) the sewage sludge disposal practice distributions to non-agricultural land
43 application and surface disposal.

- 44 (1) The value assumed for N content of sewage sludge could range from around 0.1 percent to around 17 percent
45 (McFarland 2001). Because information was not available on the distribution, a triangular distribution was
46 assumed based on IPCC guidelines.
- 47 (2) The uncertainty in the total amount of sludge applied in 2000 was based on a comparison with similar data
48 available from other publications, which were all within 3 percent of the value used in the Inventory calculations
49 (BioCycle 2000, NRC 2002, WEF 1997, Bastian 1997). The distribution was estimated to be normal based on
50 expert opinion (Boucher 2006).
- 51 (3) The uncertainty in the wastewater existing flow values for 1996 and 2000 was estimated at 0.0625 percent with a
52 lognormal distribution (Plastino 2006).

1 (4) The uncertainty in the sewage sludge disposal practice distributions was based on a comparison with similar data
2 available from other publications, which were at most 12 percent different than the distribution for non-
3 agricultural land application used in the Inventory calculations and at most 69 percent different than the
4 distribution for surface disposal used in the Inventory calculations (Biocycle 2000, NRC 2002).

5 **Other**

6 The uncertainty analysis descriptions in this section correspond to Changes in Yard Trimming and Food Scrap
7 Carbon Stocks in Landfills source category included in the Other Chapter of the Inventory.

8 **Changes in Yard Trimming and Food Scrap Carbon Stocks in Landfills**

9 The uncertainty ranges were assigned based on expert judgment and are assumed to be normally distributed
10 around the inventory estimate, except for the values for decomposition rate, proportion of C stored, and the decay rates.
11 The uncertainty ranges associated with these values are highlighted separately in this section.

12 The uncertainty range selected for input variables for the proportions of both grass and leaves in yard trimmings
13 was 20 to 60 percent. The initial C content for grass, leaves, and food scraps (all expressed as percentages in the
14 calculations for the inventory) were plus or minus 10 percent. For the moisture content of branches (where the inventory
15 estimate is 10 percent), the uncertainty range was assumed to be 5 to 30 percent, within a lognormal distribution.

16 The uncertainty ranges associated with the disposal of grass, leaves, branches, and food scraps were bound at 50
17 percent to 150 percent of the inventory estimates. The proportion of C stored in grass, leaves, branches, and food scraps
18 was assumed to vary plus or minus 20 percent from the best estimate, with a uniform distribution. The proportion of C
19 stored in food scraps was truncated at a lower bound of 2 percent.

20 Finally, the uncertainty ranges assigned to the decay rates of grass, leaves, branches, and food scraps were
21 developed based on De la Cruz, 2010. The minimum value corresponds to projected conditions if all landfills are in a dry
22 environment; the maximum value corresponds to bioreactor conditions. A triangular distribution is applied to each of these
23 variables.

24 **References**

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