ANNEX 7 Uncertainty

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 CO_2 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, CH_4 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 inventory estimation process. The U.S. plan includes procedures and guidelines, and forms and templates, for developing quantitative assessments of uncertainty in the national Inventory estimates (EPA 2002).

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

The current Inventory reflects significant improvements over the previous publication in the extent to which the Tier 2 approach to uncertainty analysis was adopted. Each of the new Tier 2 analyses reflects additional detail and characterization of input parameters using statistical data collection, expert elicitation methods and more informed judgment. In following the UNFCCC requirement under Article 4.1, emissions from International Bunker Fuels and Indirect Greenhouse Gas Emissions are not included in the total emissions estimated for the U.S. Inventory; therefore, no quantitative uncertainty estimates have been developed for these source categories.[113] Emissions from biomass combustion are accounted for implicitly in the LULUCF chapter through the calculation of changes in carbon stocks. The Energy sector does provide an estimate of CO_2 emissions from bioenergy consumption provided as a memo item for informational purposes in line with the UNFCCC reporting requirements.

Tier 1 and Tier 2 Approach

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

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

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

Characterization of Uncertainty in Input Variables

Both Tier 1 and Tier 2 uncertainty analyses require that all the input variables are well-characterized in terms of their Probability Density Functions (PDFs). In the absence of particularly convincing data measurements, sufficient data samples, or expert judgments that determined otherwise, the PDFs incorporated in the current source category uncertainty

[113] 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.

analyses were limited to normal, lognormal, uniform, triangular, and beta distributions. The choice among these five PDFs depended largely on the observed or measured data and expert judgment.

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-288 summarizes results based on assessments of source category-level uncertainty. The table presents base year (1990 or 1995) and current year (2012) 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 2012 emissions estimated for that source category. Source category trend uncertainty is described subsequently in this Appendix.

Table A-288: Summary Results of Source Category Uncertainty Analyses

Source Category	Base Year Emissions[i,a]	2012 Emissions[a]	2012 Uncertainty[b]	
	Tg CO_2 Eq.	Tg CO_2 Eq.	Low	High
CO_2	**5,076.7**	**5,382.8**	-2%	5%
Fossil Fuel Combustion[c]	4,708.9	5,071.9	-2%	5%
Non-Energy Use of Fuels	117.0	110.3	-21%	35%
Iron and Steel Production & Metallurgical Coke Production	109.8	54.3	-16%	17%
Natural Gas Systems	33.7	35.2	-19%	30%
Cement Production	33.3	35.1	-6%	6%
Lime Production	11.5	13.3	-3%	3%
Incineration of Waste	10.9	12.2	-10%	13%
Ammonia Production	16.8	9.4	-6%	7%
Other Process Uses of Carbonates	5.1	8.0	-14%	21%
Cropland Remaining Cropland	7.1	7.4	-57%	69%
Urea Consumption for Non-Agricultural Purposes	0.0	5.2	-9%	10%
Petrochemical Production	2.2	3.5	-25%	28%
Aluminum Production	6.8	3.4	-2%	2%
Soda Ash Production and Consumption	4.1	2.7	-6%	5%
Carbon Dioxide Consumption	1.4	1.8	-38%	43%
Titanium Dioxide Production	1.2	1.7	-12%	13%
Ferroalloy Production	2.2	1.7	-12%	12%
Zinc Production	0.9	1.4	-16%	17%
Glass Production	NA	1.2	-5%	4%
Phosphoric Acid Production	1.5	1.1	-19%	21%
Wetlands Remaining Wetlands	1.0	0.8	-26%	30%
Lead Production	0.3	0.5	-14%	15%
Petroleum Systems	0.4	0.4	-24%	149%
Silicon Carbide Production and Consumption	0.4	0.2	-9%	9%
Land Use, Land-Use Change, and Forestry (Sink)[d]	-841.4	-979.3	18%	-15%
Wood Biomass[e]	*0.0*	*194.1*	*NE*	*NE*
International Bunker Fuels[f]	*114.3*	*105.8*	*NE*	*NE*
Biomass – Ethanol[e]	*219.3*	*72.9*	*NE*	*NE*
CH_4	**616.6**	**567.3**	-10%	18%
Enteric Fermentation	133.2	141.0	-11%	18%
Natural Gas Systems	129.6	129.9	-19%	30%
Landfills	149.2	102.8	-56%	49%
Coal Mining	84.1	55.8	-4%	35%
Manure Management	30.4	52.9	-18%	20%
Petroleum Systems	33.9	31.7	-24%	149%
Forest Land Remaining Forest Land	4.6	15.3	-82%	176%
Wastewater Treatment	23.5	12.8	-27%	21%
Rice Cultivation	7.1	7.4	-52%	96%
Stationary Combustion	7.4	5.7	-36%	132%

Abandoned Underground Coal Mines	6.0	4.7	-19%	26%
Petrochemical Production	0.9	3.1	-10%	10%
Mobile Combustion	4.2	1.7	-12%	16%
Composting	0.3	1.6	-50%	50%
Iron and Steel Production & Metallurgical Coke Production	1.0	0.6	-21%	22%
Field Burning of Agricultural Residues	0.7	0.3	-41%	42%
Ferroalloy Production	0.0	0.0	-11%	11%
Silicon Carbide Production and Consumption	0.0	0.0	-9%	10%
Incineration of Waste	*0.0*	*0.0*	*NE*	*NE*
International Bunker Fuels[f]	*0.2*	*0.1*	*NE*	*NE*
N_2O	**315.0**	**410.1**	-8%	32%
Agricultural Soil Management	200.3	306.6	NE	NE
Stationary Combustion	12.8	22.0	-20%	51%
Manure Management	12.1	18.0	-16%	24%
Mobile Combustion	40.4	16.5	-3%	27%
Nitric Acid Production	20.0	15.3	-37%	38%
Forest Land Remaining Forest Land	0.5	12.8	-66%	146%
Adipic Acid Production	15.3	5.8	-4%	4%
Wastewater Treatment	3.7	5.0	-75%	100%
N_2O from Product Uses	4.4	4.4	-24%	24%
Composting	0.4	1.8	-50%	50%
Settlements Remaining Settlements	1.0	1.5	-49%	163%
Incineration of Waste	0.5	0.4	-48%	322%
Field Burning of Agricultural Residues	0.4	0.1	-30%	32%
Wetlands Remaining Wetlands	0.0	0.0	-73%	38%
International Bunker Fuels[f]	*1.1*	*1.0*	*NE*	*NE*
HFCs, PFCs, and SF_6	**90.5**	**161.9**	0%	13%
Substitution of Ozone Depleting Substances[g]	28.5	143.6	0%	14%
Electrical Transmission and Distribution	26.8	6.0	-18%	25%
HCFC-22 Production	36.4	4.3	-7%	10%
Semiconductor Manufacture	2.9	3.7	-5%	5%
Aluminum Production	18.5	2.5	-5%	6%
Magnesium Production	5.4	1.7	-11%	12%
Total[h]	**6,098.7**	**6,522.0**	**-1%**	**5%**
Net Emissions (Sources and Sinks)[h]	**5,257.3**	**5,542.7**	**-2%**	**7%**

Notes:
Totals may not sum due to independent rounding.
NE: Not Estimated
+ Does not exceed 0.05 Tg CO_2 Eq.
[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 2012 in this table exclude approximately 3.6 Tg CO_2 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 CO_2 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 totals.
[g] This source category's estimate for 2012 excludes 3.8 Tg of CO_2 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. .
[I] Base Year is 1990 for all sources except Substitution of Ozone Depleting Substances, for which the United States has chosen 1995.

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, CO_2 from biomass combustion, and CH_4 from incineration of waste), Tier 2 uncertainty results were used in the overall uncertainty estimation.

The overall uncertainty model results indicate that the 2012 U.S. greenhouse gas emissions are estimated to be within the range of approximately 6,448 to 6,873 Tg CO_2 Eq., reflecting a relative 95 percent confidence interval uncertainty range of -1 percent to 5 percent with respect to the total U.S. greenhouse gas emission estimate of approximately 6,522 Tg CO_2 Eq. The uncertainty interval associated with total CO_2 emissions, which constitute about 83 percent of the total U.S. greenhouse gas emissions in 2011, ranges from -2 percent to 5 percent of total CO_2 emissions estimated. The results indicate that the uncertainty associated with the inventory estimate of the total CH_4 emissions ranges from -10 percent to 18 percent, uncertainty associated with the total inventory N_2O emission estimate ranges from -8 percent to 32 percent, and uncertainty associated with high GWP gas emissions ranges from 0 percent to 13 percent.

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

Table A-289. Quantitative Uncertainty Assessment of Overall National Inventory Emissions (Tg CO_2 Eq. and Percent)

Gas	2012 Emission Estimate[a] (Tg CO_2 Eq.)	Uncertainty Range Relative to Emission Estimate[b] (Tg CO_2 Eq.)		(%)		Mean[c] (Tg CO_2 Eq.)	Standard Deviation[c] (Tg CO_2 Eq.)
		Lower Bound[d]	Upper Bound[d]	Lower Bound	Upper Bound		
CO_2	5,382.8	5,265	5,630	-2%	5%	5,448	93
CH_4[e]	567.3	513	671	-10%	18%	586	40
N_2O[e]	410.1	378	540	-8%	32%	452	41
PFC, HFC & SF_6[e]	161.9	161	182	0%	13%	172	5
Total	**6,522.0**	**6,448**	**6,873**	**-1%**	**5%**	**6,658**	**109**
Net Emissions (Sources and Sinks)	**5,542.7**	**5,420**	**5,940**	**-2%**	**7%**	**5,681**	**134**

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 3.6 Tg CO_2 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 CH_4, N_2O and high GWP gases used in the inventory emission calculations for 2012.

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., 2012) 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., 2012) 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., 2012) 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 2012, and are shown in Table A- 290.

Table A- 290. Quantitative Assessment of Trend Uncertainty (Tg CO_2 Eq. and Percent)

Gas/Source	Base Year Emissions[i,a]	2012 Emissions[a]	Emissions Trend[a]	Trend Range[a,b]	
	(Tg CO2 Eq.)		(%)	(%)	
				Lower Bound	Upper Bound
CO_2	**5,108.3**	**5,382.8**	**5%**	**1%**	**11%**
Fossil Fuel Combustion[c]	4,744.7	5,071.9	7%	2%	12%
Non-Energy Use of Fuels	120.8	110.3	-9%	-37%	35%
Iron and Steel Production & Metallurgical Coke Production	99.8	54.3	-46%	-57%	-31%
Natural Gas Systems	37.7	35.2	-7%	-34%	31%
Cement Production	33.3	35.1	5%	-4%	15%
Ammonia Production	13.0	9.4	-28%	-35%	-21%
Lime Production	11.4	13.3	17%	12%	21%
Incineration of Waste	8.0	12.2	53%	30%	81%
Cropland Remaining Cropland	7.1	7.4	4%	-60%	161%
Aluminum Production	6.8	3.4	-50%	-51%	-48%
Other Process Uses of Carbonates	4.9	8.0	63%	27%	108%
Urea Consumption for Non-Ag Purposes	3.8	5.2	39%	21%	59%
Petrochemical Production	3.4	3.5	2%	-28%	59%
Soda Ash Production and Consumption	2.7	2.7	-3%	-9%	5%
Ferroalloy Production	2.2	1.7	-23%	-35%	-8%
Phosphoric Acid Production	1.6	1.1	-31%	-48%	-7%
Glass Production	1.5	1.2	-19%	-24%	-13%
Carbon Dioxide Consumption	1.4	1.8	28%	-38%	71%
Titanium Dioxide Production	1.2	1.7	46%	13%	62%
Wetlands Remaining Wetlands	1.0	0.8	-20%	-47%	21%
Zinc Production	0.6	1.4	125%	77%	186%
Lead Production	0.5	0.5	2%	-20%	23%
Petroleum Systems	0.4	0.4	3%	-55%	136%
Silicon Carbide Production and Consumption	0.4	0.2	-58%	-68%	-58%
Land Use, Land-Use Change, and Forestry (Sink)a	-831.1	-979.3	18%	1%	38%
Biomass – Wood[e]	*214.4*	*194.1*	*-9%*	*NE*	*NE*
International Bunker Fuels[f]	*103.5*	*105.8*	*2%*	*NE*	*NE*
Biomass – Ethanol[e]	*4.2*	*72.9*	*1624%*	*NE*	*NE*
CH_4	**635.7**	**567.3**	**-11%**	**-31%**	**3%**
Natural Gas Systems	156.4	129.9	-17%	-41%	19%
Landfills	147.8	102.8	-30%	-72%	65%

Enteric Fermentation	137.9	141.0	2%	-17%	25%
Coal Mining	81.1	55.8	-31%	-56%	-33%
Petroleum Systems	35.8	31.7	-11%	-61%	103%
Manure Management	31.5	52.9	68%	13%	134%
Wastewater Treatment	13.2	12.8	-3%	-73%	-7%
Rice Cultivation	7.7	7.4	-4%	-64%	160%
Stationary Combustion	7.5	5.7	-24%	-72%	106%
Abandoned Underground Coal Mines	6.0	4.7	-22%	-51%	16%
Mobile Combustion	4.6	1.7	-63%	-70%	-54%
Forest Land Remaining Forest Land	2.5	15.3	511%	-14%	4341%
Petrochemical Production	2.3	3.1	36%	243%	554%
Iron and Steel Production & Metallurgical Coke Production	1.0	0.6	-36%	-44%	5%
Composting	0.3	1.6	397%	120%	1025%
Field Burning of Agricultural Residues	0.3	0.3	-6%	-49%	80%
Ferroalloy Production	+	+	-31%	-42%	-19%
Silicon Carbide Production and Consumption	+	+	-67%	-71%	-62%
Incineration of Waste	+	+	-23%	NE	NE
International Bunker Fuels[f]	*0.1*	*0.1*	*-37%*	*NE*	*NE*
N_2O	**398.6**	**410.1**	**3%**	**-26%**	**43%**
Agricultural Soil Management	282.1	306.6	9%	-33%	79%
Mobile Combustion	44.0	16.5	-62%	-69%	-54%
Nitric Acid Production	18.2	15.3	-16%	-58%	39%
Adipic Acid Production	15.8	5.8	-64%	-35%	-15%
Manure Management	14.4	18.0	25%	-5%	64%
Stationary Combustion	12.3	22.0	79%	13%	182%
N_2O from Product Uses	4.4	4.4	0%	-26%	28%
Wastewater Treatment	3.5	5.0	45%	-68%	553%
Forest Land Remaining Forest Land	2.1	12.8	509%	29%	2690%
Settlements Remaining Settlements	1.0	1.5	48%	-53%	378%
Incineration of Waste	0.5	0.4	-23%	-83%	259%
Composting	0.4	1.8	397%	125%	1009%
Field Burning of Agricultural Residues	0.1	0.1	2%	-34%	62%
Wetlands Remaining Wetlands	+	+	-31%	-79%	130%
International Bunker Fuels[f]	*0.9*	*1.0*	*8%*	*NE*	*NE*
HFCs, PFCs, and SF6	**121.2**	**161.9**	**34%**	**27%**	**50%**
HCFC-22 Production	36.4	4.3	-88%	-89%	-87%
Substitution of Ozone Depleting Substances	31.3	143.6	358%	317%	404%
Electrical Transmission and Distribution	26.7	6.0	-77%	-83%	-70%
Aluminum Production	18.4	2.5	-86%	-87%	-85%
Magnesium Production and Processing	5.4	1.7	-69%	-73%	-63%
Semiconductor Manufacture	2.9	3.7	28%	19%	38%
Total[h]	**6,263.8**	**6,522.0**	**4%**	**-1%**	**9%**
Net Emission (Sources and Sinks)	**5,432.7**	**5,542.7**	**2%**	**-5%**	**8%**

Notes:
Totals may not sum due to independent rounding.
NE: Not Estimated
+ Does not exceed 0.05 Tg CO_2 Eq.
[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 2011 in this table exclude approximately 3.6 Tg CO_2 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 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 CO_2 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 totals.
[g] This source category's estimate for 2011 excludes 3.8 Tg of CO_2 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. .

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

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 model uncertainty have been identified for some emission source categories, and uncertainty estimates based on their parameters' uncertainty have been developed for all the emission source categories, with the exception of CH_4 from incineration of waste, which is a minor emission source category newly added to the Inventory starting with the 2008 business year, and the international bunker fuels and wood biomass and ethanol combustion source categories, which are not included in the energy sector totals. Emissions from biomass and ethanol combustion however are accounted for implicitly in the LULUCF chapter through the calculation of changes in carbon stocks. The Energy sector does provide an estimate of CO_2 emissions from bioenergy consumption provided as a memo item for informational purposes.

Specific areas that require further research include:

- *Incorporating excluded emission sources.* Quantitative estimates for some of the sources and sinks of greenhouse gas emissions, such as from some land-use activities, industrial processes, and parts of mobile sources, could not be developed at this time either because data are incomplete or because methodologies do not exist for estimating emissions from these source categories. See Annex 5 of this report for a discussion of the sources of greenhouse gas emissions and sinks excluded from this report. In the future, efforts will focus on estimating emissions from excluded emission sources and developing uncertainty estimates for all source categories for which emissions are estimated.
- *Improving the accuracy of emission factors.* Further research is needed in some cases to improve the accuracy of emission factors used to calculate emissions from a variety of sources. For example, the accuracy of current emission factors applied to CH_4 and N_2O emissions from stationary and mobile combustion are highly uncertain.
- *Collecting detailed activity data.* Although methodologies exist for estimating emissions for some sources, problems arise in obtaining activity data at a level of detail in which aggregate emission factors can be applied. For example, the ability to estimate emissions of SF_6 from electrical transmission and distribution is limited due to a lack of activity data regarding national SF_6 consumption or average equipment leak rates.

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

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

7.4. Additional Information on Uncertainty Analyses by Source

The quantitative uncertainty estimates associated with each emission and sink source category are reported in each chapter of this Inventory following the discussions of inventory estimates and their estimation methodology. This section provides additional descriptions of the uncertainty analyses performed for some of the sources, including the models and methods used to calculate the emission estimates and the potential sources of uncertainty surrounding them. These sources are organized below in the same order as the sources in each chapter of the main section of this Inventory. To avoid repetition, the following uncertainty analysis discussions of individual source categories do not include descriptions of these source categories. Hence, to better understand the details provided below, refer to the respective chapters and sections in the main section of this Inventory, as needed. All uncertainty estimates are reported relative to the 2012 Inventory estimates for the 95 percent confidence interval, unless otherwise specified.

Energy

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

CO_2 from Fossil Fuel Combustion

For estimates of CO_2 from fossil fuel combustion, the amount of CO_2 emitted is directly related to the amount of fuel consumed, the fraction of the fuel that is oxidized, and the carbon content of the fuel. Therefore, a careful accounting of fossil fuel consumption by fuel type, average carbon contents of fossil fuels consumed, and production of fossil fuel-based products with long-term carbon storage should yield an accurate estimate of CO_2 emissions.

Nevertheless, there are uncertainties in the consumption data, carbon content of fuels and products, and carbon oxidation efficiencies. For example, given the same primary fuel type (e.g., coal, petroleum, or natural gas), the amount of carbon contained in the fuel per unit of useful energy can vary. For the United States, however, the impact of these uncertainties on overall CO_2 emission estimates is believed to be relatively small. See, for example, Marland and Pippin (1990).

Although statistics of total fossil fuel and other energy consumption are relatively accurate, the allocation of this consumption to individual end-use sectors (i.e., residential, commercial, industrial, and transportation) is less certain. For example, for some fuels the sectoral allocations are based on price rates (i.e., tariffs), but a commercial establishment may be able to negotiate an industrial rate or a small industrial establishment may end up paying an industrial rate, leading to a misallocation of emissions. Also, the deregulation of the natural gas industry and the more recent deregulation of the electric power industry have likely led to some minor problems in collecting accurate energy statistics as firms in these industries have undergone significant restructuring.

To calculate the total CO_2 emission estimate from energy-related fossil fuel combustion, the amount of fuel used in these non-energy production processes were subtracted from the total fossil fuel consumption. The amount of CO_2 emissions resulting from non-energy related fossil fuel use has been calculated separately and reported in the Carbon Emitted from Non-Energy Uses of Fossil Fuels section of this report. These factors all contribute to the uncertainty in the CO_2 estimates. Detailed discussions on the uncertainties associated with C emitted from Non-Energy Uses of Fossil Fuels can be found within that section of this chapter.

Various sources of uncertainty surround the estimation of emissions from international bunker fuels, which are subtracted from the U.S. totals (see the detailed discussions on these uncertainties provided in the International Bunker Fuels section of this chapter). Another source of uncertainty is fuel consumption by U.S. territories. The United States does not collect energy statistics for its territories at the same level of detail as for the fifty states and the District of Columbia. Therefore, estimating both emissions and bunker fuel consumption by these territories is difficult.

Uncertainties in the emission estimates presented above also result from the data used to allocate CO_2 emissions from the transportation end-use sector to individual vehicle types and transport modes. In many cases, bottom-up estimates of fuel consumption by vehicle type do not match aggregate fuel-type estimates from EIA. Further research is planned to improve the allocation into detailed transportation end-use sector emissions.

The uncertainty analysis was performed by primary fuel type for each end-use sector, using the IPCC-recommended Tier 2 uncertainty estimation methodology, Monte Carlo Stochastic Simulation technique, with @RISK software. For this uncertainty estimation, the inventory estimation model for CO_2 from fossil fuel combustion was integrated with the relevant variables from the inventory estimation model for International Bunker Fuels, to realistically

characterize the interaction (or endogenous correlation) between the variables of these two models. About 120 input variables were modeled for CO_2 from energy-related Fossil Fuel Combustion (including about 10 for non-energy fuel consumption and about 20 for International Bunker Fuels).

In developing the uncertainty estimation model, uniform distributions were assumed for all activity-related input variables and emission factors, based on the SAIC/EIA (2001) report.[114] Triangular distributions were assigned for the oxidization factors (or combustion efficiencies). The uncertainty ranges were assigned to the input variables based on the data reported in SAIC/EIA (2001) and on conversations with various agency personnel.[115]

The uncertainty ranges for the activity-related input variables were typically asymmetric around their inventory estimates; the uncertainty ranges for the emissions factors were symmetric. Bias (or systematic uncertainties) associated with these variables accounted for much of the uncertainties associated with these variables (SAIC/EIA 2001).[116] For purposes of this uncertainty analysis, each input variable was simulated 10,000 times through Monte Carlo Sampling.

CH_4 and N_2O from Stationary Combustion

Methane emission estimates from stationary sources exhibit high uncertainty, primarily due to difficulties in calculating emissions from wood combustion (i.e., fireplaces and wood stoves). The estimates of CH_4 and N_2O emissions presented are based on broad indicators of emissions (i.e., fuel use multiplied by an aggregate emission factor for different sectors), rather than specific emission processes (i.e., by combustion technology and type of emission control).

An uncertainty analysis was performed by primary fuel type for each end-use sector, using the IPCC-recommended Tier 2 uncertainty estimation methodology, Monte Carlo Stochastic Simulation technique, with @RISK software.

The uncertainty estimation model for this source category was developed by integrating the CH_4 and N_2O stationary source inventory estimation models with the model for CO_2 from fossil fuel combustion to realistically characterize the interaction (or endogenous correlation) between the variables of these three models. About 55 input variables were simulated for the uncertainty analysis of this source category (about 20 from the CO_2 emissions from fossil fuel combustion inventory estimation model and about 35 from the stationary source inventory models).

In developing the uncertainty estimation model, uniform distribution was assumed for all activity-related input variables and N_2O emission factors, based on the SAIC/EIA (2001) report.[117] For these variables, the uncertainty ranges were assigned to the input variables based on the data reported in SAIC/EIA (2001).[118] However, the CH_4 emission factors differ from those used by EIA. Since these factors were obtained from IPCC/UNEP/OECD/IEA (1997), uncertainty ranges were assigned based on IPCC default uncertainty estimates (IPCC 2000).

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[114] SAIC/EIA (2001) characterizes the underlying probability density function for the input variables as a combination of uniform and normal distributions (the former to represent the bias component and the latter to represent the random component). However, for purposes of the current uncertainty analysis, it was determined that uniform distribution was more appropriate to characterize the probability density function underlying each of these variables.

[115] In the SAIC/EIA (2001) report, the quantitative uncertainty estimates were developed for each of the three major fossil fuels used within each end-use sector; the variations within the sub-fuel types within each end-use sector were not modeled. However, for purposes of assigning uncertainty estimates to the sub-fuel type categories within each end-use sector in the current uncertainty analysis, SAIC/EIA (2001)-reported uncertainty estimates were extrapolated.

[116] Although, in general, random uncertainties are the main focus of statistical uncertainty analysis, when the uncertainty estimates are elicited from experts, their estimates include both random and systematic uncertainties. Hence, both these types of uncertainties are represented in this uncertainty analysis.

[117] SAIC/EIA (2001) characterizes the underlying probability density function for the input variables as a combination of uniform and normal distributions (the former distribution to represent the bias component and the latter to represent the random component). However, for purposes of the current uncertainty analysis, it was determined that uniform distribution was more appropriate to characterize the probability density function underlying each of these variables.

[118] In the SAIC/EIA (2001) report, the quantitative uncertainty estimates were developed for each of the three major fossil fuels used within each end-use sector; the variations within the sub-fuel types within each end-use sector were not modeled. However, for purposes of assigning uncertainty estimates to the sub-fuel type categories within each end-use sector in the current uncertainty analysis, SAIC/EIA (2001)-reported uncertainty estimates were extrapolated.

CH_4 and N_2O from Mobile Combustion

A quantitative uncertainty analysis was conducted for the mobile source sector using the IPCC-recommended Tier 2 uncertainty estimation methodology, Monte Carlo Stochastic Simulation technique, using @RISK software. The uncertainty analysis was performed on 2012 estimates of CH_4 and N_2O emissions, incorporating probability distribution functions associated with the major input variables. For the purposes of this analysis, the uncertainty was modeled for the following four major sets of input variables: (1) vehicle miles traveled (VMT) data, by on-road vehicle and fuel type and (2) emission factor data, by on-road vehicle, fuel, and control technology type, (3) fuel consumption, data, by non-road vehicle and equipment type, and (4) emission factor data, by non-road vehicle and equipment type.

Uncertainty analyses were not conducted for NO_x, CO, or NMVOC emissions. Emission factors for these gases have been extensively researched since emissions of these gases from motor vehicles are regulated in the United States, and the uncertainty in these emission estimates is believed to be relatively low. For more information, see Section 3.8. However, a much higher level of uncertainty is associated with CH_4 and N_2O emission factors due to limited emission test data, and because, unlike CO_2 emissions, the emission pathways of CH_4 and N_2O are highly complex.

Carbon Emitted from Non-Energy Uses of Fossil Fuels

An uncertainty analysis was conducted to quantify the uncertainty surrounding the estimates of emissions and storage factors from non-energy uses. This analysis, performed using @RISK software and the IPCC-recommended Tier 2 methodology (Monte Carlo Stochastic Simulation technique), provides for the specification of probability density functions for key variables within a computational structure that mirrors the calculation of the inventory estimate. The results presented below provide the 95 percent confidence interval, the range of values within which emissions are likely to fall, for this source category.

As noted above, the non-energy use analysis is based on U.S.-specific storage factors for (1) feedstock materials (natural gas, LPG, pentanes plus, naphthas, other oils, still gas, special naphthas, and other industrial coal), (2) asphalt, (3) lubricants, and (4) waxes. For the remaining fuel types (the "other" category in Table 3-20 and Table 3-21 of the main Inventory document), the storage factors were taken directly from the *IPCC Guidelines for National Greenhouse Gas Inventories*, where available, and otherwise assumptions were made based on the potential fate of carbon in the respective NEU products. To characterize uncertainty, five separate analyses were conducted, corresponding to each of the five categories. In all cases, statistical analyses or expert judgments of uncertainty were not available directly from the information sources for all the activity variables; thus, uncertainty estimates were determined using assumptions based on source category knowledge.

Incineration of Waste

A Tier 2 Monte Carlo analysis was performed to determine the level of uncertainty surrounding the estimates of CO_2 emissions and N_2O emissions from the incineration of waste (given the very low emissions for CH_4, no uncertainty estimate was derived). IPCC Tier 2 analysis allows the specification of probability density functions for key variables within a computational structure that mirrors the calculation of the inventory estimate. Uncertainty estimates and distributions for waste generation variables (i.e., plastics, synthetic rubber, and textiles generation) were obtained through a conversation with one of the authors of the Municipal Solid Waste in the United States reports. Statistical analyses or expert judgments of uncertainty were not available directly from the information sources for the other variables; thus, uncertainty estimates for these variables were determined using assumptions based on source category knowledge and the known uncertainty estimates for the waste generation variables.

The uncertainties in the waste incineration emission estimates arise from both the assumptions applied to the data and from the quality of the data. Key factors include MSW incineration rate; fraction oxidized; missing data on waste composition; average C content of waste components; assumptions on the synthetic/biogenic C ratio; and combustion conditions affecting N_2O emissions. The highest levels of uncertainty surround the variables that are based on assumptions (e.g., percent of clothing and footwear composed of synthetic rubber); the lowest levels of uncertainty surround variables that were determined by quantitative measurements (e.g., combustion efficiency, C content of C black).

Coal Mining

A quantitative uncertainty analysis was conducted for the coal mining source category using the IPCC-recommended Tier 2 uncertainty estimation methodology. Because emission estimates from underground ventilation systems were based on actual measurement data, uncertainty is relatively low. A degree of imprecision was introduced because the measurements used were not continuous but rather an average of quarterly instantaneous readings.

Additionally, the measurement equipment used can be expected to have resulted in an average of 10 percent overestimation of annual CH_4 emissions (Mutmansky & Wang 2000).

Estimates of CH_4 recovered by degasification systems are relatively certain for utilized CH_4 because of the availability of gas sales information. In addition, many coal mine operators provided information on mined-through dates for pre-drainage wells. Many of the recovery estimates use data on wells within 100 feet of a mined area. However, uncertainty exists concerning the radius of influence of each well. The number of wells counted, and thus the avoided emissions, may vary if the drainage area is found to be larger or smaller than estimated. The 2012 GHGRP data (EPA 2013) used for determining CH_4 emissions from vented degasification wells are based on weekly measurements, an improvement over the previous year's estimates, thus lowering the uncertainty of that subsource.

Abandoned Underground Coal Mines

A quantitative uncertainty analysis was conducted to estimate the uncertainty surrounding the estimates of emissions from abandoned underground coal mines. The uncertainty analysis described below provides for the specification of probability density functions for key variables within a computational structure that mirrors the calculation of the inventory estimate. The results provide the range within which, with 95 percent certainty, emissions from this source category are likely to fall.

As discussed above, the parameters for which values must be estimated for each mine in order to predict its decline curve are: 1) the coal's adsorption isotherm; 2) CH_4 flow capacity as expressed by permeability; and 3) pressure at abandonment. Because these parameters are not available for each mine, a methodological approach to estimating emissions was used that generates a probability distribution of potential outcomes based on the most likely value and the probable range of values for each parameter. The range of values is not meant to capture the extreme values, but rather values that represent the highest and lowest quartile of the cumulative probability density function of each parameter. Once the low, mid, and high values are selected, they are applied to a probability density function.

Petroleum Systems

A quantitative uncertainty analysis was conducted for previous Inventories to determine the level of uncertainty surrounding estimates of emissions from petroleum systems using the recommended methodology from IPCC. Performed using @RISK software and the IPCC-recommended Tier 2 methodology (Monte Carlo Simulation technique), this analysis provides for the specification of probability density functions for key variables within a computational structure that mirrors the calculation of the inventory estimate. The IPCC guidance notes that in using this method, "some uncertainties that are not addressed by statistical means may exist, including those arising from omissions or double counting, or other conceptual errors, or from incomplete understanding of the processes that may lead to inaccuracies in estimates developed from models." As a result, the understanding of the uncertainty of emissions estimates for this category will evolve and will improve as the underlying methodologies and datasets improve.

Performed using @RISK software and the IPCC-recommended Tier 2 methodology (Monte Carlo Stochastic Simulation technique), the method employed provides for the specification of probability density functions for key variables within a computational structure that mirrors the calculation of the inventory estimate. The results provide the range within which, with 95 percent certainty, emissions from this source category are likely to fall.

The detailed, bottom-up inventory analysis used to evaluate U.S. petroleum systems reduces the uncertainty related to the CH_4 emission estimates in comparison to a top-down approach. However, some uncertainty still remains. Emission factors and activity factors are based on a combination of measurements, equipment design data, engineering calculations and studies, surveys of selected facilities and statistical reporting. Statistical uncertainties arise from natural variation in measurements, equipment types, operational variability and survey and statistical methodologies. Published activity factors are not available every year for all 64 activities analyzed for petroleum systems; therefore, some are estimated. Because of the dominance of the seven major sources, which account for 92 percent of the total methane emissions, the uncertainty surrounding these seven sources has been estimated most rigorously, and serves as the basis for determining the overall uncertainty of petroleum systems emission estimates.

Natural Gas Systems

A quantitative uncertainty analysis was conducted for previous Inventories to determine the level of uncertainty surrounding estimates of emissions from natural gas systems using the recommended methodology from IPCC. Performed using @RISK software and the IPCC-recommended Tier 2 methodology (Monte Carlo Simulation technique), this analysis provides for the specification of probability density functions for key variables within a computational structure that mirrors the calculation of the inventory estimate. The IPCC guidance notes that in using this method, "some

uncertainties that are not addressed by statistical means may exist, including those arising from omissions or double counting, or other conceptual errors, or from incomplete understanding of the processes that may lead to inaccuracies in estimates developed from models." As a result, the understanding of the uncertainty of emissions estimates for this category will evolve and will improve as the underlying methodologies and datasets improve.

The @RISK model was used to quantify the uncertainty associated with the emissions estimates using the top twelve emission sources for the year 2009. The uncertainty analysis has not yet been updated for the 1990 through 2012 Inventory; instead, the uncertainty ranges calculated previously were applied to 2012 emissions estimates. The majority of sources in the current inventory were calculated using the same emission factors and activity data for which PDFs were developed in the 1990 through 2009 uncertainty analysis. Several emissions sources have been updated with the current Inventory, and the 2009 uncertainty ranges will not reflect the uncertainty associated with the recently updated emission factors and activity data sources. EPA plans to revise this uncertainty analysis.

International Bunker Fuels

Emission estimates related to the consumption of international bunker fuels are subject to the same uncertainties as those from domestic aviation and marine mobile combustion emissions; however, additional uncertainties result from the difficulty in collecting accurate fuel consumption activity data for international transport activities separate from domestic transport activities.[119] For example, smaller aircraft on shorter routes often carry sufficient fuel to complete several flight segments without refueling in order to minimize time spent at the airport gate or take advantage of lower fuel prices at particular airports. This practice, called tankering, when done on international flights, complicates the use of fuel sales data for estimating bunker fuel emissions. Tankering is less common with the type of large, long-range aircraft that make many international flights from the United States, however. Similar practices occur in the marine shipping industry where fuel costs represent a significant portion of overall operating costs and fuel prices vary from port to port, leading to some tankering from ports with low fuel costs.

Uncertainties exist with regard to the total fuel used by military aircraft and ships, and in the activity data on military operations and training that were used to estimate percentages of total fuel use reported as bunker fuel emissions. Total aircraft and ship fuel use estimates were developed from DoD records, which document fuel sold to the Navy and Air Force from the Defense Logistics Agency. These data may slightly over or under estimate actual total fuel use in aircraft and ships because each Service may have procured fuel from, and/or may have sold to, traded with, and/or given fuel to other ships, aircraft, governments, or other entities. There are uncertainties in aircraft operations and training activity data. Estimates for the quantity of fuel actually used in Navy and Air Force flying activities reported as bunker fuel emissions had to be estimated based on a combination of available data and expert judgment. Estimates of marine bunker fuel emissions were based on Navy vessel steaming hour data, which reports fuel used while underway and fuel used while not underway. This approach does not capture some voyages that would be classified as domestic for a commercial vessel. Conversely, emissions from fuel used while not underway preceding an international voyage are reported as domestic rather than international as would be done for a commercial vessel. There is uncertainty associated with ground fuel estimates for 1997 through 2001. Small fuel quantities may have been used in vehicles or equipment other than that which was assumed for each fuel type.

There are also uncertainties in fuel end-uses by fuel-type, emissions factors, fuel densities, diesel fuel sulfur content, aircraft and vessel engine characteristics and fuel efficiencies, and the methodology used to back-calculate the data set to 1990 using the original set from 1995. The data were adjusted for trends in fuel use based on a closely correlating, but not matching, data set. All assumptions used to develop the estimate were based on process knowledge, Department and military Service data, and expert judgments. The magnitude of the potential errors related to the various uncertainties has not been calculated, but is believed to be small. The uncertainties associated with future military bunker fuel emission estimates could be reduced through additional data collection.

Although aggregate fuel consumption data have been used to estimate emissions from aviation, the recommended method for estimating emissions of gases other than CO_2 in the 2006 IPCC Guidelines is to use data by specific aircraft type, number of individual flights and, ideally, movement data to better differentiate between domestic and international aviation and to facilitate estimating the effects of changes in technologies. The IPCC also recommends

[119] See uncertainty discussions under Carbon Dioxide Emissions from Fossil Fuel Combustion.

that cruise altitude emissions be estimated separately using fuel consumption data, while landing and take-off (LTO) cycle data be used to estimate near-ground level emissions of gases other than CO_2.[120]

There is also concern regarding the reliability of the existing DOC (2011) data on marine vessel fuel consumption reported at U.S. customs stations due to the significant degree of inter-annual variation.

Wood Biomass and Ethanol Consumption

It is assumed that the combustion efficiency for woody biomass is 100 percent, which is believed to be an overestimate of the efficiency of wood combustion processes in the United States. Decreasing the combustion efficiency would decrease emission estimates. Additionally, the heat content applied to the consumption of woody biomass in the residential, commercial, and electric power sectors is unlikely to be a completely accurate representation of the heat content for all the different types of woody biomass consumed within these sectors. Emission estimates from ethanol production are more certain than estimates from woody biomass consumption due to better activity data collection methods and uniform combustion techniques.

Industrial Processes

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

Cement Production

The uncertainties contained in these estimates are primarily due to uncertainties in the lime content of clinker and in the percentage of CKD recycled inside the cement kiln. Uncertainty is also associated with the assumption that all calcium-containing raw materials are $CaCO_3$, when a small percentage likely consists of other carbonate and non-carbonate raw materials. The lime content of clinker varies from 60 to 67 percent; 65 percent is used as a representative value (van Oss 2013a). CKD loss can range from 1.5 to 8 percent depending upon plant specifications. Additionally, some amount of CO_2 is reabsorbed when the cement is used for construction. As cement reacts with water, alkaline substances such as calcium hydroxide are formed. During this curing process, these compounds may react with CO_2 in the atmosphere to create calcium carbonate. This reaction only occurs in roughly the outer 0.2 inches of surface area. Because the amount of CO_2 reabsorbed is thought to be minimal, it was not estimated.

Lime Production

The uncertainties contained in these estimates can be attributed to slight differences in the chemical composition of lime products and recovery rates for sugar refineries and PCC manufacturers located at lime plants. Although the methodology accounts for various formulations of lime, it does not account for the trace impurities found in lime, such as iron oxide, alumina, and silica. Due to differences in the limestone used as a raw material, a rigid specification of lime material is impossible. As a result, few plants produce lime with exactly the same properties.

In addition, a portion of the CO_2 emitted during lime production will actually be reabsorbed when the lime is consumed, especially at captive lime production facilities. As noted above, lime has many different chemical, industrial, environmental, and construction applications. In many processes, CO_2 reacts with the lime to create calcium carbonate (e.g., water softening). Carbon dioxide reabsorption rates vary, however, depending on the application. For example, 100 percent of the lime used to produce precipitated calcium carbonate reacts with CO_2; whereas most of the lime used in steel making reacts with impurities such as silica, sulfur, and aluminum compounds. Quantifying the amount of CO_2 that is reabsorbed would require a detailed accounting of lime use in the United States and additional information about the associated processes where both the lime and byproduct CO_2 are "reused" are required to quantify the amount of CO_2 that

[120] U.S. aviation emission estimates for CO, NO_x, and NMVOCs are reported by EPA's National Emission Inventory (NEI) Air Pollutant Emission Trends web site, and reported under the Mobile Combustion section. It should be noted that these estimates are based solely upon LTO cycles and consequently only capture near ground-level emissions, which are more relevant for air quality evaluations. These estimates also include both domestic and international flights. Therefore, estimates reported under the Mobile Combustion section overestimate IPCC-defined domestic CO, NO_x, and NMVOC emissions by including landing and take-off (LTO) cycles by aircraft on international flights, but underestimate because they do not include emissions from aircraft on domestic flight segments at cruising altitudes. The estimates in Mobile Combustion are also likely to include emissions from ocean-going vessels departing from U.S. ports on international voyages.

is reabsorbed. Research conducted thus far has not yielded the necessary information to quantify CO_2 reabsorbtion rates.[121]

In some cases, lime is generated from calcium carbonate byproducts at pulp mills and water treatment plants.[122] The lime generated by these processes is included in the USGS data for commercial lime consumption. In the pulping industry, mostly using the Kraft (sulfate) pulping process, lime is consumed in order to causticize a process liquor (green liquor) composed of sodium carbonate and sodium sulfide. The green liquor results from the dilution of the smelt created by combustion of the black liquor where biogenic C is present from the wood. Kraft mills recover the calcium carbonate "mud" after the causticizing operation and calcine it back into lime—thereby generating CO_2—for reuse in the pulping process. Although this re-generation of lime could be considered a lime manufacturing process, the CO_2 emitted during this process is mostly biogenic in origin, and therefore is not included in the industrial processes totals (Miner and Upton 2002). In accordance with IPCC methodological guidelines, any such emissions are calculated by accounting for net carbon (C) fluxes from changes in biogenic C reservoirs in wooded or crop lands (see Chapter 7).

In the case of water treatment plants, lime is used in the softening process. Some large water treatment plants may recover their waste calcium carbonate and calcine it into quicklime for reuse in the softening process. Further research is necessary to determine the degree to which lime recycling is practiced by water treatment plants in the United States.

Uncertainties also remain surrounding recovery rates used for sugar refining and PCC production. The recovery rate for sugar refineries is based on consultation with USGS commodity expert (Miller 2013) and two sugar beet processing and refining facilities located in California that use 100 percent recovered CO_2 from lime plants (Lutter 2009). This analysis assumes that all sugar refineries located on-site at lime plants also use 100 percent recovered CO_2. The recovery rate for PCC producers located on-site at lime plants is based on the 2012 value for PCC manufactured at commercial lime plants, given by USGS (Miller 2012). However, most PCC production occurs at non-commercial lime facilities, such as paper mills. Satellite PCC plants at paper mills tend to use CO_2 produced from the paper mill (potentially biomass based). This could introduce additional uncertainty in the CO_2 estimates, because CO_2 recovered from pulp and paper facilities is mostly biogenic in origin.

Another uncertainty is the assumption that calcination emissions for LKD are around 2 percent. The National Lime association has commented that the estimates of emissions from LKD in the US could be closer to 6 percent. In addition, they note emissions may also be generated through production of other byproducts/wastes at lime plants (Seeger 2013). There is limited data publicly available on LKD generation rates and also quantities, types of other byproducts/wastes produced at lime facilities. Further research is needed to improve understanding of additional calcination emissions to consider revising the current assumptions based on the IPCC Guidelines

Other Process Uses of Carbonates

The uncertainty levels presented in this section account for uncertainty associated with activity data. Data on limestone and dolomite consumption are collected by USGS through voluntary national surveys. USGS contacts the mines (i.e., producers of various types of crushed stone) for annual sales data. Data on other carbonate consumption are not readily available. The producers report the annual quantity sold to various end-users/industry types. USGS estimates the historical response rate for the crushed stone survey to be approximately 70 percent, the rest is estimated by USGS. Large fluctuations in reported consumption exist, reflecting year-to-year changes in the number of survey responders. The uncertainty resulting from a shifting survey population is exacerbated by the gaps in the time series of reports. The accuracy of distribution by end use is also uncertain because this value is reported by the producer/mines and not the end user. Additionally, there is significant inherent uncertainty associated with estimating withheld data points for specific end uses of limestone and dolomite. Lastly, much of the limestone consumed in the United States is reported as "other unspecified uses;" therefore, it is difficult to accurately allocate this unspecified quantity to the correct end-uses.

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[121] Representatives of the National Lime Association estimate that CO_2 reabsorption that occurs from the use of lime may offset as much as a quarter of the CO_2 emissions from calcination (Males 2003).

[122] Some carbide producers may also regenerate lime from their calcium hydroxide byproducts, which does not result in emissions of CO_2. In making calcium carbide, quicklime is mixed with coke and heated in electric furnaces. The regeneration of lime in this process is done using a waste calcium hydroxide (hydrated lime) [$CaC_2 + 2H_2O \rightarrow C_2H_2 + Ca(OH)_2$], not calcium carbonate [$CaCO_3$]. Thus, the calcium hydroxide is heated in the kiln to simply expel the water [$Ca(OH)_2$ + heat $\rightarrow CaO + H_2O$] and no CO_2 is released.

Uncertainty in the estimates also arises in part due to variations in the chemical composition of limestone. In addition to calcium carbonate, limestone may contain smaller amounts of magnesia, silica, and sulfur, among other minerals. The exact specifications for limestone or dolomite used as flux stone vary with the pyrometallurgical process and the kind of ore processed.

Soda Ash Production and Consumption

Emission estimates from soda ash production have relatively low associated uncertainty levels in that reliable and accurate data sources are available for the emission factor and activity data. Soda ash production data was collected by the USGS from voluntary surveys. A survey request was sent to each of the five soda ash producers, all of which responded, representing 100 percent of the total production data (USGS 2013). One source of uncertainty is the purity of the trona ore used for manufacturing soda ash. The emission factor used for this estimate assumes the ore is 100 percent pure, and likely overestimates the emissions from soda ash manufacture. The average water-soluble sodium carbonate-bicarbonate content for ore mined in Wyoming ranges from 85.5 to 93.8 percent (USGS 1995a).The primary source of uncertainty, however, results from the fact that emissions from soda ash consumption are dependent upon the type of processing employed by each end-use. Specific emission factors for each end-use are not available, so a Tier 1 default emission factor is used for all end uses. Therefore, there is uncertainty surrounding the emission factors from the consumption of soda ash.

Glass Production

The uncertainty levels presented in this section arise in part due to variations in the chemical composition of limestone used in glass production. In addition to calcium carbonate, limestone may contain smaller amounts of magnesia, silica, and sulfur, among other minerals (potassium carbonate, strontium carbonate and barium carbonate, and dead burned dolomite). Similarly, the quality of the limestone (and mix of carbonates) used for glass manufacturing will depend on the type of glass being manufactured.

The estimates below also account for uncertainty associated with activity data. Large fluctuations in reported consumption exist, reflecting year-to-year changes in the number of survey responders. The uncertainty resulting from a shifting survey population is exacerbated by the gaps in the time series of reports. The accuracy of distribution by end use is also uncertain because this value is reported by the manufacturer of the input carbonates (limestone, dolomite & soda ash) and not the end user. For 2012, there has been no reported consumption of dolomite for glass manufacturing. This data has been reported to USGS by dolomite manufacturers and not end-users (i.e., glass manufacturers). There is a high uncertainty associated with this estimate, as dolomite is a major raw material consumed in glass production. Additionally, there is significant inherent uncertainty associated with estimating withheld data points for specific end uses of limestone and dolomite. The uncertainty of the estimates for limestone and dolomite used in glass making is especially high; however, since glass making accounts for a small percent of consumption, its contribution to the overall emissions estimate is low. Lastly, much of the limestone consumed in the United States is reported as "other unspecified uses;" therefore, it is difficult to accurately allocate this unspecified quantity to the correct end-uses. Further research is needed into alternate and more complete sources of data on carbonate-based raw material consumption by the glass industry.

Ammonia Production

The uncertainties presented in this section are primarily due to how accurately the emission factor used represents an average across all ammonia plants using natural gas feedstock. Uncertainties are also associated with ammonia production estimates and the assumption that all ammonia production and subsequent urea production was from the same process—conventional catalytic reforming of natural gas feedstock, with the exception of one ammonia production plant located in Kansas that is manufacturing ammonia from petroleum coke feedstock. Uncertainty is also associated with the representativeness of the emission factor used for the petroleum coke-based ammonia process. It is also assumed that ammonia and urea are produced at collocated plants from the same natural gas raw material.

Recovery of CO_2 from ammonia production plants for purposes other than urea production (e.g., commercial sale, etc.) has not been considered in estimating the CO_2 emissions from ammonia production, as data concerning the disposition of recovered CO_2 are not available. Such recovery may or may not affect the overall estimate of CO_2 emissions depending upon the end use to which the recovered CO_2 is applied. Further research is required to determine whether byproduct CO_2 is being recovered from other ammonia production plants for application to end uses that are not accounted for elsewhere.

Urea Consumption for Non-Agricultural Purposes

There is limited publicly available data on the quantities of urea produced and consumed for non-agricultural purposes. Therefore, the amount of urea used for non-agricultural purposes is estimated based on a balance that relies on

estimates of urea production, urea imports, urea exports, and the amount of urea used as fertilizer. The primary uncertainties associated with this source category are associated with the accuracy of these estimates as well as the fact that each estimate is obtained from a different data source. Because urea production estimates are no longer available from the USGS, there is additional uncertainty associated with urea produced beginning in 2011. There is also uncertainty associated with the assumption that all of the carbon in urea is released into the environment as CO_2 during use.

Nitric Acid Production

Uncertainty associated with the parameters used to estimate N_2O emissions includes that of production data, the share of U.S. nitric acid production attributable to each emission abatement technology over the time series, and the emission factors applied to each abatement technology type. While some information has been obtained through outreach with industry associations, limited information is available over the time series for a variety of facility level variables, including plant specific production levels, plant production technology (e.g., low, high pressure, etc.) and abatement technology type, installation date of abatement technology, and accurate destruction and removal efficiency rates.

Adipic Acid Production

Uncertainty associated with N_2O emission estimates included that of the methods used by companies to monitor and estimate emissions.

Silicon Carbide Production and Consumption

There is uncertainty associated with the emission factors used because they are based on stoichiometry as opposed to monitoring of actual SiC production plants. An alternative would be to calculate emissions based on the quantity of petroleum coke used during the production process rather than on the amount of silicon carbide produced. However, these data were not available. For CH_4, there is also uncertainty associated with the hydrogen-containing volatile compounds in the petroleum coke (IPCC 2006). There is also uncertainty associated with the use or destruction of methane generated from the process in addition to uncertainty associated with levels of production, net imports, consumption levels, and the percent of total consumption that is attributed to metallurgical and other non-abrasive uses.

Petrochemical Production

The CH_4 emission factors used for petrochemical production are based on a limited number of studies. Using plant-specific factors instead of default or average factors could increase the accuracy of the emission estimates; however, such data were not available for the current publication. There may also be other significant sources of CH_4 arising from petrochemical production activities that have not been included in these estimates.

The results of the quantitative uncertainty analysis for the CO_2 emissions from carbon black production calculation are based on feedstock consumption, import and export data, and carbon black production data. The composition of carbon black feedstock varies depending upon the specific refinery production process, and therefore the assumption that carbon black feedstock is 90 percent C gives rise to uncertainty. Also, no data are available concerning the consumption of coal-derived carbon black feedstock, so CO_2 emissions from the utilization of coal-based feedstock are not included in the emission estimate. In addition, other data sources indicate that the amount of petroleum-based feedstock used in carbon black production may be underreported by the U.S. Census Bureau. Finally, the amount of carbon black produced from the acetylene black, thermal black, and lamp black processes, although estimated to be a small percentage of the total production, is not known. Therefore, there is some uncertainty associated with the assumption that all of the carbon black is produced using the furnace black process.

Titanium Dioxide Production

Each year, USGS collects titanium industry data for titanium mineral and pigment production operations. If TiO_2 pigment plants do not respond, production from the operations is estimated on the basis of prior year production levels and industry trends. Variability in response rates varies from 67 to 100 percent of TiO_2 pigment plants over the time series. Although some TiO_2 may be produced using graphite or other carbon inputs, information and data regarding these practices were not available. Titanium dioxide produced using graphite inputs, for example, may generate differing amounts of CO_2 per unit of TiO_2 produced as compared to that generated through the use of petroleum coke in production. While the most accurate method to estimate emissions would be to base calculations on the amount of reducing agent used in each process rather than on the amount of TiO_2 produced, sufficient data were not available to do so.

As of 2004, the last remaining sulfate-process plant in the United States closed. Since annual TiO_2 production was not reported by USGS by the type of production process used (chloride or sulfate) prior to 2004 and only the percentage of total production capacity by process was reported, the percent of total TiO_2 production capacity that was

attributed to the chloride process was multiplied by total TiO_2 production to estimate the amount of TiO_2 produced using the chloride process. Finally, the emission factor was applied uniformly to all chloride-process production, and no data were available to account for differences in production efficiency among chloride-process plants. In calculating the amount of petroleum coke consumed in chloride-process TiO_2 production, literature data were used for petroleum coke composition. Certain grades of petroleum coke are manufactured specifically for use in the TiO_2 chloride process; however, this composition information was not available.

Carbon Dioxide Production

Uncertainty is associated with the number of facilities that are currently producing CO_2 from naturally occurring CO_2 reservoirs for commercial uses other than EOR, and for which the CO_2 emissions are not accounted for elsewhere. Research indicates that there are only two such facilities, which are in New Mexico and Mississippi; however, additional facilities may exist that have not been identified. In addition, it is possible that CO_2 recovery exists in particular production and end-use sectors that are not accounted for elsewhere. Such recovery may or may not affect the overall estimate of CO_2 emissions from that sector depending upon the end use to which the recovered CO_2 is applied. Further research is required to determine whether CO_2 is being recovered from other facilities for application to end uses that are not accounted for elsewhere.

Phosphoric Acid Production

Phosphate rock production data used in the emission calculations were developed by the USGS through monthly and semiannual voluntary surveys of the active phosphate rock mines during 2012. For previous years in the time series, USGS provided the data disaggregated regionally; however, beginning in 2006, only total U.S. phosphate rock production was reported. Regional production for 2012 was estimated based on regional production data from previous years and multiplied by regionally-specific emission factors. There is uncertainty associated with the degree to which the estimated 2012 regional production data represents actual production in those regions. Total U.S. phosphate rock production data are not considered to be a significant source of uncertainty because all the domestic phosphate rock producers report their annual production to the USGS. Data for exports of phosphate rock used in the emission calculation are reported by phosphate rock producers and are not considered to be a significant source of uncertainty. Data for imports for consumption are based on international trade data collected by the U.S. Census Bureau. These U.S. government economic data are not considered to be a significant source of uncertainty.

An additional source of uncertainty in the calculation of CO_2 emissions from phosphoric acid production is the carbonate composition of phosphate rock, the composition of phosphate rock varies depending upon where the material is mined, and may also vary over time. The inventory relies on one study (FIPR 2003) of chemical composition of the phosphate rock; limited data is available beyond this study. Another source of uncertainty is the disposition of the organic carbon content of the phosphate rock. A representative of the FIPR indicated that in the phosphoric acid production process, the organic carbon content of the mined phosphate rock generally remains in the phosphoric acid product, which is what produces the color of the phosphoric acid product (FIPR 2003a). Organic carbon is therefore not included in the calculation of CO_2 emissions from phosphoric acid production.

A third source of uncertainty is the assumption that all domestically-produced phosphate rock is used in phosphoric acid production and used without first being calcined. Calcination of the phosphate rock would result in conversion of some of the organic carbon in the phosphate rock into CO_2. However, according to air permit information available to the public, at least one facility has calcining units permitted for operation (NCDENR 2013).

Finally, USGS indicated that approximately 7 percent of domestically-produced phosphate rock is used to manufacture elemental phosphorus and other phosphorus-based chemicals, rather than phosphoric acid (USGS 2006). According to USGS, there is only one domestic producer of elemental phosphorus, in Idaho, and no data were available concerning the annual production of this single producer. Elemental phosphorus is produced by reducing phosphate rock with coal coke, and it is therefore assumed that 100 percent of the carbonate content of the phosphate rock will be converted to CO_2 in the elemental phosphorus production process. The calculation for CO_2 emissions is based on the assumption that phosphate rock consumption, for purposes other than phosphoric acid production, results in CO_2 emissions from 100 percent of the inorganic carbon content in phosphate rock, but none from the organic carbon content.

Iron and Steel Production and Metallurgical Coke Production

The estimates of CO_2 and CH_4 emissions from metallurgical coke production are based on material production and consumption data and average carbon contents. Uncertainty is associated with the total U.S. coking coal consumption, total U.S. coke production and materials consumed during this process. Data for coking coal consumption and metallurgical coke production are from different data sources (EIA) than data for other carbonaceous materials consumed

at coke plants (AISI), which does not include data for merchant coke plants. There is uncertainty associated with the fact that coal tar and coke breeze production were estimated based on coke production because coal tar and coke breeze production data were not available. Since merchant coke plant data is not included in the estimate of other carbonaceous materials consumed at coke plants, the mass balance equation for CO_2 from metallurgical coke production cannot be reasonably completed. Therefore, for the purpose of this analysis, uncertainty parameters are applied to primary data inputs to the calculation (i.e, coking coal consumption and metallurgical coke production) only.

The estimates of CO_2 emissions from iron and steel production are based on material production and consumption data and average carbon contents. There is uncertainty associated with the assumption that direct reduced iron and sinter consumption are equal to production. There is uncertainty associated with the assumption that all coal used for purposes other than coking coal is for direct injection coal; some of this coal may be used for electricity generation. There is also uncertainty associated with the carbon contents for pellets, sinter, and natural ore, which are assumed to equal the carbon contents of direct reduced iron. For EAF steel production, there is uncertainty associated with the amount of EAF anode and charge carbon consumed due to inconsistent data throughout the time series. Also for EAF steel production, there is uncertainty associated with the assumption that 100 percent of the natural gas attributed to "steelmaking furnaces" by AISI is process-related and nothing is combusted for energy purposes. Uncertainty is also associated with the use of process gases such as blast furnace gas and coke oven gas. Data are not available to differentiate between the use of these gases for processes at the steel mill versus for energy generation (i.e., electricity and steam generation); therefore, all consumption is attributed to iron and steel production. These data and carbon contents produce a relatively accurate estimate of CO_2 emissions. However, there are uncertainties associated with each.

For the purposes of the CH_4 calculation from iron and steel production it is assumed that all of the CH_4 escapes as fugitive emissions and that none of the CH_4 is captured in stacks or vents. Additionally, the CO_2 emissions calculation is not corrected by subtracting the carbon content of the CH_4, which means there may be a slight double counting of carbon as both CO_2 and CH_4.

Ferroalloy Production

Annual ferroalloy production is currently reported by the USGS in three broad categories: ferroalloys containing 25 to 55 percent silicon (including miscellaneous alloys), ferroalloys containing 56 to 95 percent silicon, and silicon metal (through 2005 only). Silicon metal production values for 2006 through 2012 are assumed to be equal to the 2005 value reported by USGS (USGS did not report silicon metal production for 2006 through 2012). Ferrosilicon production values for 2011 and 2012 are assumed to be equal to the 2010 value reported by USGS (USGS did not report ferrosilicon production for 2011 and 2012). It was assumed that the IPCC emission factors apply to all of the ferroalloy production processes, including miscellaneous alloys. Finally, production data for silvery pig iron (alloys containing less than 25 percent silicon) are not reported by the USGS to avoid disclosing proprietary company data. Emissions from this production category, therefore, were not estimated.

Also, some ferroalloys may be produced using wood or other biomass as a primary or secondary carbon source (carbonaceous reductants), information and data regarding these practices were not available. Emissions from ferroalloys produced with wood or other biomass would not be counted under this source because wood-based carbon is of biogenic origin.[123] Even though emissions from ferroalloys produced with coking coal or graphite inputs would be counted in national trends, they may be generated with varying amounts of CO_2 per unit of ferroalloy produced. The most accurate method for these estimates would be to base calculations on the amount of reducing agent used in the process, rather than the amount of ferroalloys produced. These data, however, were not available, and are also often considered confidential business information.

Emissions of CH_4 from ferroalloy production will vary depending on furnace specifics, such as type, operation technique, and control technology. Higher heating temperatures and techniques such as sprinkle charging will reduce CH_4 emissions; however, specific furnace information was not available or included in the CH_4 emission estimates.

Aluminum Production

Uncertainty was assigned to the CO_2, CF_4, and C_2F_6 emission values reported by each individual facility to EPA's GHGRP. As previously mentioned, the methods for estimating emissions for EPA's GHGRP and this report are the same, and follow the IPCC (2006) methodology. As a result, it was possible to assign uncertainty bounds (and

[123] Emissions and sinks of biogenic carbon are accounted for in the Land Use, Land-Use Change, and Forestry chapter.

distributions) based on an analysis of the uncertainty associated with the facility-specific emissions estimated for previous inventory years. Uncertainty surrounding the reported CO_2, CF_4, and C_2F_6 emission values were determined to have a normal distribution with uncertainty ranges of ±6, ±16, and ±20 percent, respectively. A Monte Carlo analysis was applied to estimate the overall uncertainty of the CO_2, CF_4, and C_2F_6 emission estimates for the U.S. aluminum industry as a whole, and the results are provided below.

Magnesium Production

To estimate the uncertainty surrounding the estimated 2012 SF_6 emissions from magnesium production and processing, the uncertainties associated with three variables were estimated: (1) emissions reported by magnesium producers and processors for 2012 through EPA's GHGRP, (2) emissions estimated for magnesium producers and processors that reported via the Partnership in prior years but did not report 2012 emissions through EPA's GHGRP, and (3) emissions estimated for magnesium producers and processors that did not participate in the Partnership or report through EPA's GHGRP. An uncertainty of 5 percent was assigned to the SF_6 emissions (usage) data reported by each GHGRP reporter (per the 2006 IPCC Guidelines). If facilities did not report emissions data during the current reporting year through EPA's GHGRP reporting program, SF_6 emissions data were held constant at the most recent available value reported through the Partnership. The uncertainty associated with these values was estimated to be 30 percent for each year of extrapolation. One known sand caster (the lone Partner) has not reported since 2007 and its activity and emission factor were held constant at 2005 levels due to a reporting anomaly in 2006 because of malfunctions at the facility. The uncertainty associated with the SF_6 usage for the sand casting Partner was 74 percent. For those industry processes that are not represented in Partnership, such as permanent mold and wrought casting, SF_6 emissions were estimated using production and consumption statistics reported by USGS and estimated process-specific emission factors (see Table 4-81 in the main Inventory document). The uncertainties associated with the emission factors and USGS-reported statistics were assumed to be 75 percent and 25 percent, respectively. Emissions associated with die casting and sand casting activities utilized emission factors based on Partner reported data with an uncertainties of 75 percent. In general, where precise quantitative information was not available on the uncertainty of a parameter, a conservative (upper-bound) value was used.

Additional uncertainties exist in these estimates that are not addressed in this methodology, such as the basic assumption that SF_6 neither reacts nor decomposes during use. The melt surface reactions and high temperatures associated with molten magnesium could potentially cause some gas degradation. Previous measurement studies have identified SF_6 cover gas degradation in die casting applications on the order of 20 percent (Bartos et al. 2007). Sulfur hexafluoride may also be used as a cover gas for the casting of molten aluminum with high magnesium content; however, the extent to which this technique is used in the United States is unknown.

Zinc Production

The uncertainties contained in these estimates are two-fold, relating to activity data and emission factors used. First, there is uncertainty associated with the amount of EAF dust consumed in the United States to produce secondary zinc using emission-intensive Waelz kilns. The estimate for the total amount of EAF dust consumed in Waelz kilns is based on (1) an EAF dust consumption value reported annually by Horsehead Corporation as part of its financial reporting to the Securities and Exchange Commission (SEC), and (2) an EAF dust consumption value obtained from the Waelz kiln facility operated in Alabama by Steel Dust Recycling LLC. Since actual EAF dust consumption information is not available for PIZO's facility (2009-2010) and SDR's facility (2008-2010), the amount is estimated by multiplying the EAF dust recycling capacity of the facility (available from the company's Web site) by the capacity utilization factor for Horsehead Corporation (which is available from Horsehead's financial reports). Also, the EAF dust consumption for PIZO's facility in 2011 was estimated by multiplying the average capacity utilization factor developed from Horsehead Corp. and SDR's annual capacity utilization rates by PIZO's EAF dust recycling capacity. Therefore, there is uncertainty associated with the assumption used to estimate PIZO and SDR's annual EAF dust consumption values (except SDR's EAF dust consumption in 2011 which was obtained from SDR's recycling facility in Alabama).

Second, there are uncertainties associated with the emission factors used to estimate CO_2 emissions from secondary zinc production processes. The Waelz kiln emission factors are based on materials balances for metallurgical coke and EAF dust consumed as provided by Viklund-White (2000). Therefore, the accuracy of these emission factors depend upon the accuracy of these materials balances. Data limitations prevented the development of emission factors for the electrothermic process. Therefore, emission factors for the Waelz kiln process were applied to both electrothermic and Waelz kiln production processes.

Lead Production

Uncertainty associated with lead production relates to the emission factors and activity data used. The direct smelting emission factor used in primary production is taken from Sjardin (2003) who averaged the values provided by three other studies (Dutrizac et al. 2000, Morris et al. 1983, Ullman 1997). For secondary production, Sjardin (2003) added a CO_2 emission factor associated with battery treatment. The applicability of these emission factors to plants in the United States is uncertain. There is also a smaller level of uncertainty associated with the accuracy of primary and secondary production data provided by the USGS.

HCFC-22 Production

The uncertainty analysis presented in this section was based on a plant-level Monte Carlo Stochastic Simulation for 2006. The Monte Carlo analysis used estimates of the uncertainties in the individual variables in each plant's estimating procedure. This analysis was based on the generation of 10,000 random samples of model inputs from the probability density functions for each input. A normal probability density function was assumed for all measurements and biases except the equipment leak estimates for one plant; a log-normal probability density function was used for this plant's equipment leak estimates. The simulation for 2006 yielded a 95-percent confidence interval for U.S. emissions of 6.8 percent below to 9.6 percent above the reported total.

The relative errors yielded by the Monte Carlo Stochastic Simulation for 2006 were applied to the U.S. emission estimate for 2012. The resulting estimates of absolute uncertainty are likely to be reasonably accurate because (1) the methods used by the three plants to estimate their emissions are not believed to have changed significantly since 2006, and (2) although the distribution of emissions among the plants may have changed between 2006 and 2012 (because both HCFC-22 production and the HFC-23 emission rate declined significantly), the two plants that contribute significantly to emissions were estimated to have similar relative uncertainties in their 2006 (as well as 2005) emission estimates. Thus, changes in the relative contributions of these two plants to total emissions are not likely to have a large impact on the uncertainty of the national emission estimate.

Substitution of Ozone Depleting Substances

Given that emissions of ODS substitutes occur from thousands of different kinds of equipment and from millions of point and mobile sources throughout the United States, emission estimates must be made using analytical tools such as the Vintaging Model or the methods outlined in IPCC (2006). Though the model is more comprehensive than the IPCC default methodology, significant uncertainties still exist with regard to the levels of equipment sales, equipment characteristics, and end-use emissions profiles that were used to estimate annual emissions for the various compounds.

The Vintaging Model estimates emissions from 60 end-uses. The uncertainty analysis, however, quantifies the level of uncertainty associated with the aggregate emissions resulting from the top 21 end-uses, comprising over 95 percent of the total emissions, and 6 other end-uses. These 27 end-uses comprise 97 percent of the total emissions, equivalent to 143.6 Tg CO_2 Eq. In an effort to improve the uncertainty analysis, additional end-uses are added annually, with the intention that over time uncertainty for all emissions from the Vintaging Model will be fully characterized. Any end-uses included in previous years' uncertainty analysis were included in the current uncertainty analysis, whether or not those end-uses were included in the top 95 percent of emissions from ODS Substitutes.

In order to calculate uncertainty, functional forms were developed to simplify some of the complex "vintaging" aspects of some end-use sectors, especially with respect to refrigeration and air-conditioning, and to a lesser degree, fire extinguishing. These sectors calculate emissions based on the entire lifetime of equipment, not just equipment put into commission in the current year, thereby necessitating simplifying equations. The functional forms used variables that included growth rates, emission factors, transition from ODSs, change in charge size as a result of the transition, disposal quantities, disposal emission rates, and either stock for the current year or original ODS consumption. Uncertainty was estimated around each variable within the functional forms based on expert judgment, and a Monte Carlo analysis was performed. The most significant sources of uncertainty for this source category include the emission factors for refrigerated transport, as well as the percent of non-MDI aerosol propellant that is HFC-152a.

Semiconductor Manufacture

A quantitative uncertainty analysis of this source category was performed using the IPCC-recommended Tier 2 uncertainty estimation methodology, the Monte Carlo Stochastic Simulation technique. The equation used to estimate uncertainty is:

$$\text{Total Emissions } (E_T) = \text{GHGRP Reported Emissions } (E_R) + \text{Non-GHGRP Reporters Emissions } (E_{NR})$$

where E_R and E_{NR} denote totals for the indicated subcategories of emissions.

The uncertainty in E_T presented in Table 4-97 in the main Inventory document below results from the convolution of two distributions of emissions, each reflecting separate estimates of possible values of E_R and E_{NR}. The approach and methods for estimating each distribution and combining them to arrive at the reported 95 percent CI are described in the remainder of this section.

The uncertainty estimate of E_R, or GHGRP reported emissions, is developed based on gas-specific uncertainty estimates of emissions for two representative model facilities, one processing 200 mm wafers and one processing 300 mm wafers. Uncertainties in emissions for each gas and model facility were developed during the assessment of emission estimation methods for the subpart I GHGRP rulemaking in 2012 (see *Technical Support for Modifications to the Fluorinated Greenhouse Gas Emission Estimation Method Option for Semiconductor Facilities under Subpart* I, docket EPA–HQ–OAR–2011–0028).[124] This analysis did not take into account the use of abatement. For the model facility that processed 200 mm wafers, estimates of uncertainties at a 95 percent CI ranged from ±29 percent for C_3F_8 to ±10 percent for CF_4. For the corresponding model 300 mm facility, estimates of the 95 percent CI ranged from ±36 percent for C_4F_8 to ±16 percent for CF_4. These gas and wafer-specific uncertainty estimates are applied for facilities that did not abate emissions as reported under EPA's GHGRP.

For those facilities reporting abatement of emissions under EPA's GHGRP, estimates of uncertainties for the no abatement model facilities are modified to reflect the use of full abatement (abatement of *all* gases from *all* cleaning and etching equipment) and partial abatement. These assumptions used to develop uncertainties for the partial and full abatement facilities are identical for 200 mm and 300 mm wafer processing facilities. For all facilities reporting gas abatement, a triangular distribution of destruction or removal efficiency is assumed for each gas. For facilities reporting partial abatement, the distribution of destruction efficiencies, for each gas, is assumed to be right triangularly distributed. Consideration of abatement then resulted in four additional model facilities, two (model) 200 mm wafer-processing facilities (one fully and one partially abating each gas) and two (model) 300 mm wafer-processing facilities (one fully and the other partially abating each gas). Gas-specific emission uncertainties were estimated by convolving the distributions of unabated emissions with the appropriate distribution of abatement efficiency for fully and partially abated facilities using a Montel Carlo simulation.

The uncertainty in E_R is obtained by mapping GHGRP-reported gas and wafer-specific emissions to one of the six described model facilities, and then running a Monte Carlo simulation which results in the 95 percent CI for GHGRP reporting facilities (E_R).

The estimate of uncertainty in E_{NR} entailed developing estimates of uncertainties for the emissions factors for each non-reporting sub-category and the corresponding estimates of TMLA.

The uncertainty in TMLA depends on the uncertainty of two variables – an estimate of the uncertainty in the average annual capacity utilization for each level of production of fabs (e.g., full scale or R&D production) and a corresponding estimate of the uncertainty in the number of layers manufactured. For both variables, the distributions of capacity utilizations and number of manufactured layers are assumed triangular for all categories of non-reporting fabs. For production fabs the most probable utilization is assumed to be 89 percent, with the highest and lowest utilization assumed to be 95 percent and 70 percent, respectively. The corresponding values for facilities that manufacture discrete devices are, 84 percent, 95 percent, and 73 percent, respectively, while the values for utilization for R&D facilities, are assumed to be 20 percent, 30 percent, and 10 percent, respectively. For the triangular distributions that govern the number of possible layers manufactured, it is assumed the most probable value is one layer less than reported in the ITRS; the

[124] On November 13, 2013, EPA published a final rule revising subpart I (Electronics Manufacturing) of the GHGRP (78 FR 68162). The revised rule includes updated default emission factors and updated default destruction and removal efficiencies that are slightly different from those that semiconductor manufacturers were required to use to report their 2012 emissions. The uncertainty analyses that were performed during the development of the revised rule focused on these updated defaults, but are expected to be reasonably representative of the uncertainties associated with the older defaults, particularly for estimates at the country level. (They may somewhat underestimate the uncertainties associated with the older defaults at the facility level.) For simplicity, the 2012 estimates are assumed to be unbiased although in some cases, the updated (and therefore more representative) defaults are higher or lower than the older defaults. Multiple models and sensitivity scenarios were run for the subpart I analysis. The uncertainty analysis presented here made use of the Input gas and wafer size model (Model 1) under the following conditions: Year = 2010, f = 20, n = SIA3.

smallest number varied by technology generation between one and two layers less than given in the ITRS and largest number of layers corresponded to the figure given in the ITRS.

The uncertainty bounds for the average capacity utilization and the number of layers manufactured are used as inputs in a separate Monte Carlo simulation to estimate the uncertainty around the TMLA of both individual facilities as well as the total non-reporting TMLA of each sub-population.

The uncertainty around the emission factors for each non-reporting category of facilities is dependent on the uncertainty of the total emissions ($MMTCO_2e$ units) and the TMLA of each reporting facility in that category. For each subpopulation of reporting facilities, total emissions were regressed on TMLA (with an intercept forced to zero) for 10,000 emissions and 10,000 TMLA values in a Monte Carlo simulation, which results in 10,000 total regression coefficients (emission factors). The 2.5th and the 97.5th percentile of these emission factors are determined and the bounds are assigned as the percent difference from the estimated emission factor.

For simplicity, the results of the Monte Carlo simulations on the bounds of the gas- and wafer size-specific emissions as well as the TMLA and emission factors are assumed to be normally distributed and the uncertainty bounds are assigned at 1.96 standard deviations around the estimated mean. The departures from normality were observed to be small.

The final step in estimating the uncertainty in emissions of non-reporting facilities is convolving the distribution of emission factors with the distribution of TMLA using Monte Carlo simulation.

Electrical Transmission and Distribution

To estimate the uncertainty associated with emissions of SF_6 from Electrical Transmission and Distribution, uncertainties associated with four quantities were estimated: (1) emissions from Partners, (2) emissions from GHGRP-Only Reporters, (3) emissions from Non-Reporters, and (4) emissions from manufacturers of electrical equipment. A Monte Carlo analysis was then applied to estimate the overall uncertainty of the emissions estimate.

Total emissions from the SF_6 Emission Reduction Partnership include emissions from both reporting (through the Partnership or GHGRP) and non-reporting Partners. For reporting Partners, individual Partner-reported SF_6 data was assumed to have an uncertainty of 10 percent. Based on a Monte Carlo analysis, the cumulative uncertainty of all Partner-reported data was estimated to be 2.5 percent. The uncertainty associated with extrapolated or interpolated emissions from non-reporting Partners was assumed to be 20 percent.

For GHGRP-Only Reporters, reported SF_6 data was assumed to have an uncertainty of 20 percent.[125] Based on a Monte Carlo analysis, the cumulative uncertainty of all GHGRP-Only reported data was estimated to be 5.2 percent.

There are two sources of uncertainty associated with the regression equations used to estimate emissions in 2012 from Non-Reporters: (1) uncertainty in the coefficients (as defined by the regression standard error estimate), and (2) the uncertainty in total transmission miles for Non-Reporters. Uncertainties were also estimated regarding (1) the quantity of SF_6 supplied with equipment by equipment manufacturers, which is projected from Partner provided nameplate capacity data and industry SF_6 nameplate capacity estimates, and (2) the manufacturers' SF_6 emissions rate.

Solvent and Other Product Use

The uncertainty analysis descriptions in this section correspond to source categories included in the Solvent and Other Product Use Chapter of the Inventory.

Nitrous Oxide from Product Uses

The overall uncertainty associated with the 2012 N_2O emission estimate from N_2O product usage was calculated using the IPCC Guidelines for National Greenhouse Gas Inventories (2006) Tier 2 methodology. Uncertainty associated with the parameters used to estimate N_2O emissions include production data, total market share of each end use, and the emission factors applied to each end use, respectively.

[125] Uncertainty is assumed to be higher for the GHGRP-Only category, because 2011 is the first year that those utilities have reported to EPA.

Agriculture

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

Enteric Fermentation

A quantitative uncertainty analysis for this source category was performed using the IPCC-recommended Tier 2 uncertainty estimation methodology based on a Monte Carlo Stochastic Simulation technique as described in ICF (2003). These uncertainty estimates were developed for the 1990 through 2001 Inventory report (i.e., 2003 submission to the UNFCCC). There have been no significant changes to the methodology since that time; consequently, these uncertainty estimates were directly applied to the 2012 emission estimates in this report.

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

Manure Management

An analysis (ERG 2003a) was conducted for the manure management emission estimates presented in the 1990 through 2001 Inventory report (i.e., 2003 submission to the UNFCCC) to determine the uncertainty associated with estimating CH_4 and N_2O emissions from livestock manure management. The quantitative uncertainty analysis for this source category was performed in 2002 through the IPCC-recommended Tier 2 uncertainty estimation methodology, the Monte Carlo Stochastic Simulation technique. The uncertainty analysis was developed based on the methods used to estimate CH_4 and N_2O emissions from manure management systems. A normal probability distribution was assumed for each source data category. The series of equations used were condensed into a single equation for each animal type and state. The equations for each animal group contained four to five variables around which the uncertainty analysis was performed for each state. These uncertainty estimates were directly applied to the 2012 emission estimates as there have not been significant changes in the methodology since that time.

Rice Cultivation

The largest uncertainty in the calculation of CH_4 emissions from rice cultivation is associated with the emission factors. Seasonal emissions, derived from field measurements in the United States, vary by more than one order of magnitude. This inherent variability is due to differences in cultivation practices, particularly fertilizer type, amount, and mode of application; differences in cultivar type; and differences in soil and climatic conditions. A portion of this variability is accounted for by separating primary from ratooned areas. However, even within a cropping season or a given management regime, measured emissions may vary significantly. Of the experiments used to derive the emission factors applied here, primary emissions ranged from 61 to 500 kg CH_4/hectare-season and ratoon emissions ranged from 481 to 1,490 kg CH_4/hectare-season. The uncertainty distributions around the California winter flooding, California non-winter flooding, non-California primary, and ratoon emission factors were derived using the distributions of the relevant emission factors available in the literature and described above. Variability around the rice emission factor means was not normally distributed for any crops, but rather skewed, with a tail trailing to the right of the mean. A lognormal statistical distribution was, therefore, applied in the Tier 2 Monte Carlo analysis.

Other sources of uncertainty include the primary rice-cropped area for each state, percent of rice-cropped area that is ratooned, the length of the growing season, and the extent to which flooding outside of the normal rice season is practiced. Expert judgment was used to estimate the uncertainty associated with primary rice-cropped area for each state at 1 to 5 percent, and a normal distribution was assumed. Uncertainties were applied to ratooned area by state, based on the level of reporting performed by the state. Within California, the uncertainty associated with the percentage of rice fields that are winter flooded was estimated at plus and minus 20 percent. No uncertainty estimates were calculated for the practice of flooding outside of the normal rice season outside of California because CH_4 flux measurements have not been undertaken over a sufficient geographic range or under a broad enough range of representative conditions to account for this source in the emission estimates or its associated uncertainty.

Agricultural Soil Management

Uncertainty was estimated for each of the following five components of N_2O emissions from agricultural soil management: (1) direct emissions simulated by DAYCENT; (2) the components of indirect emissions (N volatilized and leached or runoff) simulated by DAYCENT; (3) direct emissions approximated with the IPCC (2006) Tier 1 method; (4) the components of indirect emissions (N volatilized and leached or runoff) approximated with the IPCC (2006) Tier 1 method; and (5) indirect emissions estimated with the IPCC (2006) Tier 1 method. Uncertainty in direct emissions, which account for the majority of N_2O emissions from agricultural management, as well as the components of indirect emissions calculated by DAYCENT were estimated with a Monte Carlo Analysis, addressing uncertainties in model inputs and structure (i.e., algorithms and parameterization) (Del Grosso et al. 2010). Uncertainties in direct emissions calculated with the IPCC (2006) Tier 1 method, the proportion of volatilization and leaching or runoff estimated with the IPCC (2006) Tier 1 method, and indirect N_2O emissions were estimated with a simple error propagation approach (IPCC 2006). Uncertainties from the Tier 1 and Tier 3 (i.e., DAYCENT) estimates were combined using simple error propagation (IPCC 2006). Additional details on the uncertainty methods are provided in Annex 3.11.

Field Burning of Agricultural Residues

Due to data and time limitations, uncertainty resulting from burning of Kentucky bluegrass and "other" residues are not included in the emissions estimates and not incorporated into the uncertainty analysis.

Land Use, Land-Use Change, and Forestry

The uncertainty analysis descriptions in this section correspond to source categories included in the Land Use, Land-Use Change, and Forestry Chapter of the Inventory.

Forest Land Remaining Forest Land

The uncertainty analysis descriptions in this section correspond to source categories included in the Forest Land Remaining Forest Land sub-chapter of Land Use, Land-Use Change, and Forestry Chapter of the Inventory.

Changes in Forest Carbon Stocks

A quantitative uncertainty analysis placed bounds on current flux for forest ecosystems as well as C in harvested wood products through Monte Carlo Stochastic Simulation of the Methods described above and probabilistic sampling of C conversion factors and inventory data. See Annex 3.13 for additional information.

Non-CO_2 Emissions from Forest Fires

Non-CO_2 gases emitted from forest fires depend on several variables, including: forest area for Alaska and the lower 48 states; average C densities for wildfires in Alaska, wildfires in the lower 48 states, and prescribed fires in the lower 48 states; emission ratios; and combustion factor values (proportion of biomass consumed by fire). To quantify the uncertainties for emissions from forest fires, a Monte Carlo (Tier 2) uncertainty analysis was performed using information about the uncertainty surrounding each of these variables.

Direct N_2O fluxes from Forest Soils

The amount of N_2O emitted from forests depends not only on N inputs and fertilized area, but also on a large number of variables, including organic C availability, oxygen gas partial pressure, soil moisture content, pH, temperature, and tree planting/harvesting cycles. The effect of the combined interaction of these variables on N_2O flux is complex and highly uncertain. IPCC (2006) does not incorporate any of these variables into the default methodology, except variation in estimated fertilizer application rates and estimated areas of forested land receiving N fertilizer. All forest soils are treated equivalently under this methodology. Furthermore, only synthetic N fertilizers are captured, so applications of organic N fertilizers are not estimated. However, the total quantity of organic N inputs to soils is included in the Agricultural Soil Management and *Settlements Remaining Settlements* sections.

Uncertainties exist in the fertilization rates, annual area of forest lands receiving fertilizer, and the emission factors. Fertilization rates were assigned a default level[126] of uncertainty at ±50 percent, and area receiving fertilizer was assigned a ±20 percent according to expert knowledge (Binkley 2004). IPCC (2006) provided estimates for the uncertainty associated with direct N_2O emission factor for synthetic N fertilizer application to soils. Quantitative uncertainty of this source category was estimated through the IPCC-recommended Tier 2 uncertainty estimation

[126] Uncertainty is unknown for the fertilization rates so a conservative value of ±50 percent was used in the analysis.

methodology. The uncertainty ranges around the 2005 activity data and emission factor input variables were directly applied to the 2012 emissions estimates.

Cropland Remaining Cropland

The uncertainty analysis descriptions in this section correspond to source categories included in the Cropland Remaining Cropland sub-chapter of Land Use, Land-Use Change, and Forestry Chapter of the Inventory.

Agricultural Soil Carbon Stock Change

Uncertainty associated with the *Cropland Remaining Cropland* land-use category was addressed for changes in agricultural soil C stocks (including both mineral and organic soils). Uncertainty estimates are presented in Table 7-22 in the main Inventory document for each subsource (mineral soil C stocks and organic soil C stocks) and method that was used in the inventory analysis (i.e., Tier 2 and Tier 3). Uncertainty for the portions of the Inventory estimated with Tier 2 and 3 approaches was derived using a Monte Carlo approach (see Annex 3.12 for further discussion). Uncertainty estimates from each approach were combined using the error propagation equation in accordance with IPCC (2006). The combined uncertainty was calculated by taking the square root of the sum of the squares of the standard deviations of the uncertain quantities.

CO_2 Emissions from Agricultural Liming

Uncertainty regarding limestone and dolomite activity data inputs was estimated at ±15 percent and assumed to be uniformly distributed around the inventory estimate (Tepordei 2003b, Willett 2013b). Analysis of the uncertainty associated with the emission factors included the following: the fraction of agricultural lime dissolved by nitric acid versus the fraction that reacts with carbonic acid, and the portion of bicarbonate that leaches through the soil and is transported to the ocean. Uncertainty regarding the time associated with leaching and transport was not accounted for, but should not change the uncertainty associated with CO_2 emissions (West 2005). The uncertainties associated with the fraction of agricultural lime dissolved by nitric acid and the portion of bicarbonate that leaches through the soil were each modeled as a smoothed triangular distribution between ranges of zero percent to 100 percent. The uncertainty surrounding these two components largely drives the overall uncertainty estimates reported below. More information on the uncertainty estimates for Liming of Agricultural Soils is contained within the Uncertainty Annex.

CO_2 Emissions from Urea Fertilization

A Tier 2 Monte Carlo analysis was completed. The largest source of uncertainty was the default emission factor, which assumes that 100 percent of the C in $CO(NH_2)_2$ applied to soils is ultimately emitted into the environment as CO_2. This factor does not incorporate the possibility that some of the C may be retained in the soil. The emission estimate is, therefore, likely to be high. In addition, each urea consumption data point has an associated uncertainty. Urea for non-fertilizer use, such as aircraft deicing, may be included in consumption totals; it was determined through personal communication with Fertilizer Regulatory Program Coordinator David L. Terry (2007), however, that this amount is most likely very small. Research into aircraft deicing practices also confirmed that urea is used minimally in the industry; a 1992 survey found a known annual usage of approximately 2,000 tons of urea for deicing; this would constitute 0.06 percent of the 1992 consumption of urea (EPA 2000). Similarly, surveys conducted from 2002 to 2005 indicate that total urea use for deicing at U.S. airports is estimated to be 3,740 MT per year, or less than 0.07 percent of the fertilizer total for 2007 (Itle 2009). Lastly, there is uncertainty surrounding the assumptions behind the calculation that converts fertilizer years to calendar years.

Land Converted to Cropland

Uncertainty analysis for mineral soil C stock changes using the Tier 3 and Tier 2 approaches were based on the same method described for *Cropland Remaining Cropland*. The uncertainty for annual C emission estimates from drained organic soils in *Land Converted to Cropland* was estimated using the Tier 2 approach, as described in the *Cropland Remaining Cropland* section.

Uncertainty for the portions of the Inventory estimated with Tier 2 and 3 approaches was derived using a Monte Carlo approach (see Annex 3.12 for further discussion). Uncertainty estimates from each approach were combined using the error propagation equation in accordance with IPCC (2006), i.e., by taking the square root of the sum of the squares of the standard deviations of the uncertain quantities.

Grassland Remaining Grassland

Uncertainty for the portions of the Inventory estimated with Tier 2 and 3 approaches was derived using a Monte Carlo approach (see Annex 3.12 for further discussion). Uncertainty estimates from each approach were combined using

the error propagation equation in accordance with IPCC (2006), i.e., by taking the square root of the sum of the squares of the standard deviations of the uncertain quantities.

Land Converted to Grassland

Uncertainty for the portions of the Inventory estimated with Tier 2 and 3 approaches was derived using a Monte Carlo approach (see Annex 3.12 for further discussion). Uncertainty estimates from each approach were combined using the error propagation equation in accordance with IPCC (2006) (i.e., by taking the square root of the sum of the squares of the standard deviations of the uncertain quantities).

Wetlands Remaining Wetlands

The uncertainty analysis descriptions in this section correspond to source categories included in the Wetlands Remaining Wetlands sub-chapter of Land Use, Land-Use Change, and Forestry Chapter of the Inventory.

Peatlands Remaining Peatlands

The uncertainty associated with peat production data was estimated to be ± 25 percent (Apodaca 2008) and assumed to be normally distributed. The uncertainty associated with peat production data stems from the fact that the USGS receives data from the smaller peat producers but estimates production from some larger peat distributors. The peat type production percentages were assumed to have the same uncertainty values and distribution as the peat production data (i.e., ± 25 percent with a normal distribution). The uncertainty associated with the Alaskan reported production data was assumed to be the same as the lower 48 states, or ± 25 percent with a normal distribution. It should be noted that the Alaska Department of Natural Resources estimates that around half of producers do not respond to their survey with peat production data; therefore, the production numbers reported are likely to underestimate Alaska peat production (Szumigala 2008). The uncertainty associated with the average bulk density values was estimated to be ± 25 percent with a normal distribution (Apodaca 2008). IPCC (2006) gives uncertainty values for the emissions factors for the area of peat deposits managed for peat extraction based on the range of underlying data used to determine the emission factors. The uncertainty associated with the emission factors was assumed to be triangularly distributed. The uncertainty values surrounding the C fractions were based on IPCC (2006) and the uncertainty was assumed to be uniformly distributed. Based on these values and distributions, a Monte Carlo (Tier 2) uncertainty analysis was applied to estimate the uncertainty of CO_2 and N_2O emissions from *Peatlands Remaining Peatlands*.

Settlements Remaining Settlements

The uncertainty analysis descriptions in this section correspond to source categories included in the Settlements Remaining Settlements sub-chapter of Land Use, Land-Use Change, and Forestry Chapter of the Inventory.

Changes in Carbon Stocks in Urban Trees

Uncertainty associated with changes in C stocks in urban trees includes the uncertainty associated with urban area, percent urban tree coverage, and estimates of gross and net C sequestration for each of the 50 states and the District of Columbia. A 10 percent uncertainty was associated with urban area estimates based on expert judgment. Uncertainty associated with estimates of percent urban tree coverage for each of the 50 states was based on standard error estimates reported by Nowak and Greenfield (2012). Uncertainty associated with estimate of percent urban tree coverage for the District of Columbia was based on the standard error estimate reported by Nowak et al. (2013). Uncertainty associated with estimates of gross and net C sequestration for each of the 50 states and the District of Columbia was based on standard error estimates for each of the state-level sequestration estimates reported by Nowak et al. (2013). These estimates are based on field data collected in each of the 50 states and the District of Columbia, and uncertainty in these estimates increases as they are scaled up to the national level.

Additional uncertainty is associated with the biomass equations, conversion factors, and decomposition assumptions used to calculate C sequestration and emission estimates (Nowak et al. 2002). These results also exclude changes in soil C stocks, and there may be some overlap between the urban tree C estimates and the forest tree C estimates. Due to data limitations, urban soil flux is not quantified as part of this analysis, while reconciliation of urban tree and forest tree estimates will be addressed through the land-representation effort described in the Planned Improvements section of this chapter.

Direct N2O Fluxes from Settlement Soils

The amount of N_2O emitted from settlements depends not only on N inputs and fertilized area, but also on a large number of variables, including organic C availability, oxygen gas partial pressure, soil moisture content, pH, temperature, and irrigation/watering practices. The effect of the combined interaction of these variables on N_2O flux is complex and

highly uncertain. The IPCC default methodology does not explicitly incorporate any of these variables, except variations in fertilizer N and sewage sludge application rates. All settlement soils are treated equivalently under this methodology.

Uncertainties exist in both the fertilizer N and sewage sludge application rates in addition to the emission factors. Uncertainty in fertilizer N application was assigned a default level of ±50 percent.[127] Uncertainty in the amounts of sewage sludge applied to non-agricultural lands and used in surface disposal was derived from variability in several factors, including: (1) N content of sewage sludge; (2) total sludge applied in 2000; (3) wastewater existing flow in 1996 and 2000; and (4) the sewage sludge disposal practice distributions to non-agricultural land application and surface disposal. Uncertainty in the emission factors was provided by the IPCC (2006).

Other

The uncertainty analysis descriptions in this section correspond to source categories included in the Other sub-chapter of Land Use, Land-Use Change, and Forestry Chapter of the Inventory.

Changes in Yard Trimming and Food Scrap Carbon Stocks in Landfills

The uncertainty analysis for landfilled yard trimmings and food scraps includes an evaluation of the effects of uncertainty for the following data and factors: disposal in landfills per year (tons of C), initial C content, moisture content, decay rate, and proportion of C stored. The C storage landfill estimates are also a function of the composition of the yard trimmings (i.e., the proportions of grass, leaves and branches in the yard trimmings mixture). There are respective uncertainties associated with each of these factors.

Waste

The uncertainty analysis descriptions in this section correspond to source categories included in the Waste Chapter of the Inventory.

Landfills

Several types of uncertainty are associated with the estimates of CH_4 emissions from MSW and industrial waste landfills. The primary uncertainty concerns the characterization of landfills. Information is not available on two fundamental factors affecting CH_4 production: the amount and composition of waste placed in every MSW and industrial waste landfill for each year of its operation. The SOG survey is the only nationwide data source that compiles the amount of MSW disposed at the state-level. The surveys do not include information on waste composition and there are no comprehensive data sets that compile quantities of waste disposed or waste composition by landfill. Some MSW landfills have conducted detailed waste composition studies, but landfills in the United States are not required to perform these types of studies. The approach used here assumes that the CH_4 generation potential and the rate of decay that produces CH_4, as determined from several studies of CH_4 recovery at MSW landfills, are representative of conditions at U.S. landfills. When this top-down approach is applied at the nationwide level, the uncertainties are assumed to be less than when applying this approach to individual landfills and then aggregating the results to the national level. In other words, this approach may over- and under-estimate CH_4 generation at some landfills if used at the facility-level, but the end result is expected to balance out because it is being applied nationwide. There is also a high degree of uncertainty and variability associated with the first order decay model, particularly when a homogeneous waste composition and hypothetical decomposition rates are applied to heterogeneous landfills (IPCC 2006).

Additionally, there is a lack of landfill-specific information regarding the number and type of industrial waste landfills in the United States. The approach used here assumes that the majority (99 percent) of industrial waste disposed of in industrial waste landfills consists of waste from the pulp and paper and food and beverage industries. However, because waste generation and disposal data are not available in an existing data source for all U.S. industrial waste landfills, we apply a straight disposal factor over the entire time series to the amount of waste generated to determine the amounts disposed.

Aside from the uncertainty in estimating CH_4 generation potential, uncertainty exists in the estimates of the landfill gas oxidized. A constant oxidation factor of 10 percent as recommended by the Intergovernmental Panel on Climate Change (IPCC) for managed landfills is used for both MSW and industrial waste landfills regardless of climate, the type of cover material, and/or presence of a gas collection system. The number of field studies measuring the rate of

[127] No uncertainty is provided with the USGS fertilizer consumption data (Ruddy et al. 2006) so a conservative ±50% was used in the analysis.

oxidation has increased substantially since the IPCC 2006 Guidelines were published and, as discussed in the Potential Improvements section, efforts are being made to review the literature and revise this value based on recent, peer-reviewed studies.

Another significant source of uncertainty lies with the estimates of CH_4 that are recovered by flaring and gas-to-energy projects at MSW landfills. Three separate databases containing recovery information are used to determine the total amount of CH_4 recovered and there are uncertainties associated with each. The LMOP database and the flare vendor databases are updated annually, while the EIA database has not been updated since 2005 and will essentially be replaced by GHGRP data for a portion of landfills (i.e., those meeting the GHGRP thresholds). To avoid double counting and to use the most relevant estimate of CH_4 recovery for a given landfill, a hierarchical approach is used among the three databases. The EIA data are given precedence because CH_4 recovery was directly reported by landfills, the LMOP data are given second priority because CH_4 recovery is estimated from facility-reported LFGTE system characteristics, and the flare data are given third priority because this database contains minimal information about the flare and no site-specific operating characteristics (Bronstein et al., 2012). The IPCC default value of 10 percent for uncertainty in recovery estimates was used in the uncertainty analysis when metering of landfill gas was in place (for about 64 percent of the CH_4 estimated to be recovered). This 10 percent uncertainty factor applies to 2 of the 3 databases (EIA and LMOP). For flaring without metered recovery data (approximately 34 percent of the CH_4 estimated to be recovered), a much higher uncertainty of approximately 50 percent was used (e.g., when recovery was estimated as 50 percent of the flare's design capacity).

Wastewater Treatment

The overall uncertainty associated with both the 2012 CH_4 and N_2O emission estimates from wastewater treatment and discharge was calculated using the IPCC Good Practice Guidance Tier 2 methodology (2000). Uncertainty associated with the parameters used to estimate CH_4 emissions include that of numerous input variables used to model emissions from domestic wastewater, and wastewater from pulp and paper manufacture, meat and poultry processing, fruits and vegetable processing, ethanol production, and petroleum refining. Uncertainty associated with the parameters used to estimate N_2O emissions include that of sewage sludge disposal, total U.S. population, average protein consumed per person, fraction of N in protein, non-consumption nitrogen factor, emission factors per capita and per mass of sewage-N, and for the percentage of total population using centralized wastewater treatment plants.

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