

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

Some of the current inventory estimates, such as those for CO₂ Emissions from Fossil Fuel Combustion for example, have a relatively low level of uncertainty associated with them. Other categories of emissions exist, however, for which the inventory emission estimates are considered less certain. The major types of uncertainty associated with these inventory 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 evaluated by comparing model results with those of other models developed to characterize the same emission (or removal) process and through sensitivity analysis. However, it would be very difficult—if not impossible—to quantify the model uncertainty associated with the inventory 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 estimates and is the main focus of the quantitative uncertainty analyses in this report. Parameter uncertainty has been quantified for most of the emission sources in the U.S. Inventory.

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 QA/QC and uncertainty management plan in accordance with the IPCC *Good Practice Guidance*. Like the quality assurance/quality control 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 (EPA 2002). 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.

1 The IPCC *Good Practice Guidance* recommends two approaches—Tier 1 and Tier 2—for developing
 2 quantitative estimates of uncertainty in the inventory estimate of individual source categories and the overall
 3 inventory. Of these, the Tier 2 approach is both more flexible and more powerful than Tier 1; both methods are
 4 described in the next section. The United States is currently in the process of implementing a multi-year strategy to
 5 develop quantitative estimates of uncertainty for all source categories using the Tier 2 approach. This year, a Tier 2
 6 approach was implemented for all source categories except HCFC-22 production.

7 The current Inventory reflects significant improvements over the previous publication in the extent to
 8 which the Tier 2 approach to uncertainty analysis was adopted. For the current Inventory, the Tier 1 approach was
 9 only adopted for one source category (i.e., HCFC-22 production). Each of the new Tier 2 analyses reflect additional
 10 detail and characterization of input parameters using statistical data collection, expert elicitation methods and more
 11 informed judgment. Emissions and sinks from International Bunker Fuels, Biomass Combustion, and Indirect
 12 Greenhouse Gas Emissions are not included in total emissions estimated for the U.S. Inventory; therefore, no
 13 quantitative uncertainty estimates have been developed for these source categories.

14 Tier 1 and Tier 2 Approach

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

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

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

34 Characterization of Uncertainty in Input Variables

35 Both Tier 1 and Tier 2 uncertainty analyses require that all the input variables are well-characterized in
 36 terms of their Probability Distribution Functions (PDFs). In the absence of particularly convincing data
 37 measurements, sufficient data samples, or expert judgments that determined otherwise, the PDFs incorporated in the
 38 current source category uncertainty analyses were limited to uniform, triangular, lognormal, or normal. The choice
 39 among these four PDFs depended largely on the observed or measured data and expert judgment.

40 Source Category Inventory Uncertainty Estimates

41 Discussion surrounding the input parameters and sources of uncertainty for each source category appears in
 42 the body of this report. Table A- 242 summarizes results based on assessments of source category-level uncertainty.
 43 The table presents base year (1990 or 1995) and current year (2005) emissions for each source category. The
 44 combined uncertainty for each source category is expressed as a percent of the total 2005 emissions estimated for
 45 that source category. Source category trend uncertainty is described below.

46 **Table A- 242: Summary Results of Source Category Uncertainty Analyses**

Base Year	2005	2005 Uncertainty
-----------	------	------------------

Source Category	Emissions*		Emissions	
	Tg CO ₂ Eq.	Tg CO ₂ Eq.	Low	High
CO₂	5,061.7	6,091.2	-2%	5%
Fossil Fuel Combustion	4,724.1	5,752.8	-2%	5%
Non-Energy Use of Fuels	117.2	142.3	-20%	-8%
Natural Gas Systems	33.7	28.2	-26%	30%
Cement Manufacture	33.3	45.9	-13%	13%
Lime Manufacture	11.3	13.7	-8%	8%
Limestone and Dolomite Use	5.5	7.4	-6%	6%
Soda Ash Manufacture and Consumption	4.1	4.2	-7%	7%
Carbon Dioxide Consumption	1.4	1.3	-16%	21%
Municipal Solid Waste Combustion	10.9	20.9	-26%	19%
Titanium Dioxide Production	1.3	1.9	-16%	16%
Aluminum Production	6.8	4.2	-5%	5%
Iron and Steel Production	85.0	45.4	-10%	26%
Ferroalloy Production	2.2	1.4	-13%	13%
Ammonia Manufacture and Urea Application	19.3	16.3	-8%	8%
Phosphoric Acid Production	1.5	1.4	-18%	19%
Petrochemical Production	2.2	2.9	-34%	41%
Silicon Carbide Production and Consumption	0.4	0.2	-10%	10%
Lead Production	0.3	0.3	-16%	17%
Zinc Production	0.9	0.5	-22%	25%
Land-Use, Land Change, and Forestry (Sink) ^a	(712.9)	(828.4)		
<i>Cropland Remaining Cropland</i>	(31.0)	(36.4)	-43%	38%
<i>Land Converted to Cropland</i>	8.7	7.2	-33%	29%
<i>Grassland Remaining Grassland</i>	0.1	16.1	-18%	15%
<i>Land Converted to Grassland</i>	(14.6)	(16.3)	-13%	14%
<i>Urban Trees</i>	(57.5)	(88.5)	-23%	19%
<i>Changes in Forest Carbon Stocks</i>	(497.6)	(788.4)	-27%	27%
<i>International Bunker Fuels^b</i>	113.7	95.6		
<i>Wood Biomass and Ethanol Combustion^b</i>	219.3	206.5		
CH₄	609.1	539.3	-10%	16%
Stationary Combustion	8.0	6.9	-30%	112%
Mobile Combustion	4.7	2.6	-6%	6%
Coal Mining	81.9	52.4	-5%	12%
Abandoned Underground Coal Mines	6.0	5.5	-16%	18%
Natural Gas Systems	124.5	111.1	-26%	30%
Petroleum Systems	34.4	28.5	-24%	148%
Petrochemical Production	0.9	1.1	-8%	9%
Silicon Carbide Production and Consumption	+	+	-9%	9%
Iron and Steel Production	1.3	1.0	-8%	8%
Ferroalloy Production	+	+	-12%	12%
Enteric Fermentation	115.7	112.1	-11%	18%
Manure Management	30.9	41.3	-18%	20%
Rice Cultivation	7.1	6.9	-70%	170%
Field Burning of Agricultural Residues	0.7	0.9	-13%	13%
Forest Land Remaining Forest Land	7.1	11.6	-71%	92%
Landfills	161.0	132.0	-39%	32%
Wastewater Treatment	24.8	25.4	-38%	47%
<i>International Bunker Fuels^b</i>	0.2	0.1		
N₂O	482.0	468.7	-16%	24%
Stationary Combustion	12.3	13.8	-22%	189%
Mobile Combustion	43.7	38.0	-18%	19%
Adipic Acid Production	15.2	6.0	-46%	47%
Nitric Acid Production	17.8	15.7	-16%	18%
Manure Management	8.6	9.5	-16%	24%
Agricultural Soil Management	366.9	365.1		
<i>Direct</i>	310.1	310.5	-20%	22%
<i>Indirect</i>	56.8	54.6	-42%	135%
Field Burning of Agricultural Residues	0.4	0.5	-11%	12%
Wastewater Treatment	6.4	8.0	-79%	93%

N ₂ O Product Usage	4.3	4.3	-4%	4%
Municipal Solid Waste Combustion	0.5	0.5	-74%	153%
Settlements Remaining Settlements	5.1	5.8	-49%	163%
Forest Land Remaining Forest Land	0.8	1.5	-57%	86%
<i>International Bunker Fuels^b</i>	<i>1.0</i>	<i>0.9</i>		
HFCs, PFCs, and SF₆	89.3	163.0	-6%	16%
Substitution of Ozone Depleting Substances	0.3	123.3	-9%	20%
Aluminum Production	18.5	3.0	-7%	7%
HCFC-22 Production	35.0	16.5	-10%	10%
Semiconductor Manufacture	2.9	4.3	-21%	20%
Electrical Transmission and Distribution	27.1	13.2	-6%	7%
Magnesium Production and Processing	5.4	2.7	-4%	4%
Total	6,242.1	7,262.3	-1%	5%
Net Emission (Sources and Sinks)	5,529.1	6,443.9		

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

+ Does not exceed 0.05 Tg CO₂ Eq.

^a Sinks are only included in net emissions total.

^b Emissions from International Bunker Fuels and Biomass Combustion are not included in totals.

Note: Totals may not sum due to independent rounding.

Overall (Aggregate) Inventory Uncertainty Estimate

The overall uncertainty estimate for the U.S. greenhouse gas emissions inventory was developed using the IPCC Tier 2 uncertainty estimation methodology. The Monte Carlo simulation output data from each emission source category uncertainty analysis was combined and the probability distribution of each fitted to the combined output data. This was done using the source category-specific simulation output data (i.e., detail from each of the total number of iterations) 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 HCFC-22 production source category, Tier 1 uncertainty results were used in the overall uncertainty analysis estimation. However, for all other emission sources (excluding international bunker fuels, CO₂ from biomass combustion), Tier 2 uncertainty results were used in the overall uncertainty estimation.

The results from the overall uncertainty model results indicate that the 2005 U.S. greenhouse gas emissions are estimated to be within the range of 7,169.2 to 7,638.9 Tg CO₂ Eq., reflecting a relative 95 percent confidence interval uncertainty range of -1.3 percent to 5.2 percent with respect to the total U.S. greenhouse gas emissions estimate of 7,262.3 Tg CO₂ Eq. The uncertainty interval associated with total CO₂ emissions, which constitute about 84 percent of the total U.S. greenhouse gas emissions in 2005, ranges from -1.7 percent to 5.1 percent of total CO₂ emissions estimated. The results indicate that the uncertainty associated with the inventory estimate of the total N₂O emissions is the largest (-16.4 percent to 23.6 percent), followed by the total inventory CH₄ emission estimate (-9.5 percent to 15.7 percent), and high GWP gas emissions (-6.0 percent to 15.6 percent).

A summary of the overall quantitative uncertainty estimates are shown below, in Table A- 243.

Table A- 243. Quantitative Uncertainty Assessment of Overall National Inventory Emissions (Tg CO₂ Eq. and Percent)

Gas	2005 Emission Estimate (Tg CO ₂ Eq.)	Uncertainty Range Relative to Emission Estimate ^a				Mean ^b (Tg CO ₂ Eq.)	Standard Deviation (Tg CO ₂ Eq.)
		Lower Bound ^c		Upper Bound ^c			
		Lower Bound ^c	Upper Bound ^c	Lower Bound ^c	Upper Bound ^c		
CO ₂	6,091.2	5,989.4	6,400.5	-1.7%	5.1%	6,191.5	107.2
CH ₄	539.3	488.0	623.8	-9.5%	15.7%	554.0	34.3
N ₂ O	468.7	392.0	579.4	-16.4%	23.6%	485.2	47.6
PFC, HFC & SF ₆ ^d	163.0	153.2	188.5	-6.0%	15.6%	170.1	9.2
Total	7,262.3	7,169.2	7,638.9	-1.3%	5.2%	7,400.8	122.6

Notes:

^a Range of emission estimates for a 95 percent confidence interval.

^b 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.

1 ^c The low and high estimates for total emissions were separately calculated through simulations and, hence, the low and high emission estimates for the sub-
2 source categories do not sum to total emissions.

3 ^d The overall uncertainty estimate did not take into account the uncertainty in the GWP values for CH₄, N₂O and high GWP gases used in the inventory emission
4 calculations for 2004.

5 **Trend Uncertainty**

6 In addition to estimates of uncertainty associated with the current year's emission estimates, this Annex
7 also presents estimates of trend uncertainty. The *IPCC Good Practice Guidance* defines trend as the difference in
8 emissions between the base year (i.e., 1990) and the current year (i.e., 2005) inventory estimates. However, for
9 purposes of understanding the concept of trend uncertainty, the emission trend is defined in this report as the
10 percentage change in the emissions (or removal) estimated for the current year, relative to the emission (or removal)
11 estimated for the base year. The uncertainty associated with this emission trend is referred to as trend uncertainty.

12 Under the Tier 1 approach, the trend uncertainty for a source category is estimated using the sensitivity of
13 the calculated difference between base year and 2005 emissions to an incremental (i.e., 1 percent) increase in one or
14 both of these values for that source category. The two sensitivities are expressed as percentages: Type A sensitivity
15 highlights the effect on the difference between the base and the current year emissions caused by a 1 percent change
16 in both, while Type B sensitivity highlights the effect caused by a change to only the current year's emissions. Both
17 sensitivities are simplifications introduced in order to analyze correlation between base and current year estimates.
18 Once calculated, the two sensitivities are combined using the error propagation equation to estimate overall trend
19 uncertainty.

20 Under the Tier 2 approach, the trend uncertainty is estimated using Monte Carlo Stochastic Simulation
21 technique. The trend uncertainty analysis takes into account the fact that base and the current year estimates often
22 share input variables. For purposes of the current Inventory, a simple approach has been adopted, under which the
23 base year source category emissions (or removals) are assumed to exhibit the same uncertainty characteristics as the
24 current year emissions (or removals). Source category-specific PDFs for base year estimates were developed using
25 2004 uncertainty output data. These were adjusted to account for differences in magnitude between the two years'
26 inventory estimates. Then, for each source category, a trend uncertainty estimate was developed using the Monte
27 Carlo method. The overall inventory trend uncertainty estimate was developed by combining all source category-
28 specific trend uncertainty estimates. These preliminary trend uncertainty estimates present the range of likely
29 change from base year to 2005, and are shown in Table A- 244.

1 **Table A- 244. Quantitative Assessment of Trend Uncertainty (Tg CO₂ Eq. and Percent)**

Gas/Source	Emissions		Trend	Trend Range ^a	
	Base Year*	2005		Lower Bound	Upper Bound
	(Tg CO ₂ Eq.)	(Tg CO ₂ Eq.)	(%)	(%)	(%)
CO₂	5,061.1	6,091.2	20%	15%	26%
Fossil Fuel Combustion	4,723.7	5,752.8	22%	16%	28%
Non-Energy Use of Fossil Fuels	117.2	142.3	21%	-2%	52%
Natural Gas Systems	33.7	28.185	-16%	-44%	25%
Cement Manufacture	33.3	45.9	38%	14%	66%
Lime Manufacture	11.2	13.7	22%	8%	36%
Limestone and Dolomite Use	5.5	7.4	34%	22%	46%
Soda Ash Manufacture and Consumption	4.1	4.2	2%	-8%	14%
Carbon Dioxide Consumption	1.4	1.3	-6%	-28%	21%
Waste Combustion	10.9	20.9	92%	37%	171%
Titanium Dioxide Production	1.3	1.9	47%	16%	85%
Aluminum Production	6.8	4.208	-38%	-42%	-34%
Iron and Steel Production	85.0	45.4	-47%	-58%	-32%
Ferroalloy Production	2.2	1.4	-35%	-46%	-22%
Ammonia Production and Urea Application	19.3	16.3	-15%	-24%	-5%
Phosphoric Acid Production	1.5	1.4	-10%	-31%	18%
Petrochemical Production	2.2	2.9	30%	-25%	125%
Silicon Carbide Production and Consumption	0.4	0.2	-42%	-49%	-32%
Lead Production	0.3	0.3	-7%	-27%	17%
Zinc Production	1.0	0.5	-54%	-67%	-36%
<i>Land-Use Change and Forestry (Sink)^a</i>	<i>(890.6)</i>	<i>(828.4)</i>	<i>-7%</i>		
CH₄	609.0	539.3	-11%	-25%	6%
Stationary Combustion	8.0	6.9	-13%	-64%	106%
Mobile Combustion	4.8	2.6	-45%	-50%	-40%
Coal Mining	81.9	52.4	-36%	-43%	-28%
Abandoned Coal Mines	6.0	5.5	-8%	-28%	17%
Natural Gas Systems	124.5	111.1	-11%	-40%	34%
Petroleum Systems	34.4	28.5	-17%	-64%	90%
Petrochemical Production	0.9	1.1	25%	11%	41%
Silicon Carbide Production and Consumption	+	+	-67%	-71%	-62%
Iron and Steel Production	1.3	1.0	-28%	-36%	-19%
Ferroalloy Production	+	+	-43%	-52%	-32%
Enteric Fermentation	115.7	112.1	-3%	-21%	20%
Manure Management	30.9	41.3	34%	2%	75%
Rice Cultivation	7.1	6.9	-3%	-81%	372%
Field Burning of Agricultural Residues	0.7	0.9	24%	4%	49%
Forest Land Remaining Forest Land	7.1	11.6	64%	-58%	519%
Landfills	161.0	132.0	-18%	-53%	43%
Wastewater Treatment	24.8	25.4	3%	-38%	71%
<i>International Bunker Fuels^b</i>	<i>0.2</i>	<i>0.1</i>	<i>-36%</i>		
N₂O	417.3	468.7	12%	-15%	47%
Stationary Combustion	12.3	13.8	12%	-61%	230%
Mobile Combustion	43.7	38.0	-13%	-33%	14%
Adipic Acid Production	15.2	6.0	-61%	-81%	-19%
Nitric Acid Production	17.8	15.7	-12%	-31%	12%
Manure Management	8.6	9.5	10%	-16%	45%
Agricultural Soil Management	302.4	365.1	21%	-16%	73%
Field Burning of Agricultural Residues	0.4	0.5	36%	16%	60%
Wastewater Treatment	6.4	8.0	26%	-57%	281%
N ₂ O Product Usage	4.3	4.3	0%	-6%	5%
Municipal Solid Waste Combustion	0.5	0.5	12%	-79%	502%
Settlements Remaining Settlements	5.1	5.8	13%	-66%	272%
Forest Land Remaining Forest Land	0.8	1.5	98%	-24%	410%
<i>Forest Soils</i>	<i>0.1</i>	<i>0.3</i>	<i>556%</i>		
<i>Forest Fires</i>	<i>0.7</i>	<i>1.2</i>	<i>64%</i>		
<i>International Bunker Fuels^b</i>	<i>1.0</i>	<i>0.9</i>	<i>-10%</i>		

HFCs, PFCs, and SF₆	89.3	163.0	83%	66%	112%
Substitution of Ozone Depleting Substances	0.3	123.3	36899%	30356%	45120%
Aluminum Production	18.5	3.0	-84%	-86%	-82%
HCFC-22 Production	35.0	16.5	-53%	-59%	-46%
Semiconductor Manufacture	2.9	4.3	48%	10%	98%
Electrical Transmission and Distribution	27.1	13.2	-51%	-60%	-41%
Magnesium Production and Processing	5.4	2.7	-51%	-54%	-48%
Total	6,176.7	7,262.3		12%	23%
Net Emission (Sources and Sinks)	5,286.1	6,433.9			

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

+ Does not exceed 0.05 Tg CO₂ Eq.

^a Trend Range represents the 95% confidence interval for the change in emissions from Base Year to 2004.

^b Sinks are only included in net emissions total.

^c Emissions from International Bunker Fuels and Biomass Combustion are not included in totals.

Note: Totals may not sum due to independent rounding.

7.3. Planned Improvements

Identifying the sources of uncertainties 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 uncertainties 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 sources, and preliminary uncertainty estimates based on their parameters' uncertainty have been developed for most of the emission source categories.

Specific areas that require further research include:

- *Incorporating excluded emission sources.* Quantitative estimates of the uncertainty associated with some of the sources and sinks of greenhouse gas emissions are not available at this time. In the future, efforts will focus on developing uncertainty estimates for all source categories for which emissions or removals 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 CH₄ and N₂O 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 SF₆ from electrical transmission and distribution is limited due to a lack of activity data regarding national SF₆ 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. In some cases, this might involve using measured or published statistics rather than relying on expert judgment if such data is 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. This would then improve the analysis of trend uncertainty, replacing the simplifying assumptions described in the “Trend Uncertainty” section above.

7.4. Additional Information on Uncertainty Analyses by Source

The information below provides further discussion of the uncertainty analyses performed for some of the sources, including more detailed descriptions of models and methods used to calculate the emission estimates and the potential sources of uncertainty surrounding them.

Energy

Mobile Combustion (excluding CO₂)

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

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

The estimates of VMT for highway vehicles by vehicle type in the United States provided by FHWA are subject to several possible sources of error, such as unregistered vehicles, as well as measurement and estimation errors. These VMT were apportioned by fuel type, based on data from DOE (2006), and then allocated to individual model years using temporal profiles of both the vehicle fleet by age and vehicle usage by model year in the United States provided by EPA (2006b) and EPA (2000). While the uncertainty associated with total U.S. VMT is believed to be low, the uncertainty within individual source categories was assumed to be higher given uncertainties associated with apportioning total VMT into individual vehicle categories, by fuel type, by technology type, and equipment age. The uncertainty of individual estimates was assumed to relate to the magnitude of estimated VMT (i.e., it was assumed smaller sources had greater percentage uncertainty). A further source of uncertainty occurs since FHWA and EPA use different definitions of vehicle type and estimates of VMT by vehicle type (provided by FHWA) are broken down by fuel type using EPA vehicle categories.

A total of 75 highway data input variables were modeled through Monte Carlo Simulation using @RISK software. Variables included VMT and emission factors for individual vehicle categories and technologies. In developing the uncertainty estimation model, a normal distribution was assumed for all activity-related input variables (e.g., VMT) except in the case of buses, in which a triangular distribution was used. The dependencies and other correlations among the activity data were incorporated into the model to ensure consistency in the model specification and simulation. Emission factors were assigned uniform distributions, with upper and lower bounds assigned to input variables based on 97.5 percent confidence intervals of laboratory test data. In cases where data did not yield statistically significant results within the 95 percent confidence interval, estimates of upper and lower bounds were made using expert judgment. The results of this analysis are reported in the section below, titled *Quantitative Estimates of Uncertainty*.

Emissions from non-highway vehicles are a small portion of total emissions from mobile sources, representing 24 percent of CH₄ emissions from mobile sources and 11 percent of N₂O emissions from mobile sources in 2005. Since they comprise a small share of mobile source emissions, even large uncertainties in these estimates would have a relatively small impact on the total emission estimate for mobile sources. As a result, a quantitative analysis of uncertainty of emissions from non-highway vehicles has not been performed. However, sources of uncertainty for non-highway vehicles are being investigated by examining the underlying uncertainty of emission factors and fuel consumption data, and in the future, EPA will consider conducting a quantitative analysis of uncertainty for these sources.

Fuel consumption for off-highway vehicles (i.e., equipment used for agriculture, construction, lawn and garden, railroad, airport ground support, etc., as well as recreational vehicles) was generated by EPA’s NONROAD

1 model (EPA 2006d). This model estimates fuel consumption based on estimated equipment/vehicle use (in hours)
 2 and average fuel consumed per hour of use. Since the fuel estimates are not based upon documented fuel sales or
 3 consumption, a fair degree of uncertainty accompanies these estimates.

4 Estimates of distillate fuel sales for ships and boats were obtained from EIA's *Fuel Oil and Kerosene Sales*
 5 (EIA 1991 through 2006). These estimates have a moderate level of uncertainty since EIA's estimates are based on
 6 survey data and reflect sales to economic sectors, which may include use by both mobile and non-mobile sources
 7 within a sector. Domestic consumption of residual fuel by ships and boats is obtained from EIA (2005a). These
 8 estimates fluctuate widely from year to year, and are believed to be highly uncertain. In addition, estimates of
 9 distillate and residual fuel sales for ships and boats are adjusted for bunker fuel consumption, which introduces an
 10 additional (and much higher) level of uncertainty.

11 Jet fuel and aviation gasoline consumption data are obtained from EIA (2006b) and FAA (2006b).
 12 Estimates of jet fuel consumption are also adjusted downward to account for international bunker fuels, introducing
 13 a significant amount of uncertainty. Additionally, all jet fuel consumption in the transportation sector is assumed to
 14 be consumed by aircraft. Some fuel purchased by airlines is not used in aircraft but instead used to power auxiliary
 15 power units, in ground equipment, and to test engines. Some jet fuel may also be used for other purposes such as
 16 blending with diesel fuel or heating oil.

17 In calculating CH₄ emissions from aircraft, an average emission factor is applied to total jet fuel
 18 consumption. This average emission factor takes into account the fact that CH₄ emissions occur only during the
 19 landing and take-off (LTO) cycles, with no CH₄ being emitted during the cruise cycle. However, a better approach
 20 would be to apply emission factors based on the number of LTO cycles.

21 **Municipal Solid Waste Combustion**

22 The uncertainty upper and lower bounds of the CO₂ emissions estimate for Municipal Solid Waste
 23 Combustion were 19 percent and -26 percent respectively, and for N₂O emissions estimate were 153 percent and -
 24 74 percent respectively, at the 95% confidence interval. The uncertainties in the waste combustion emission
 25 estimates arise from both the assumptions applied to the data and from the quality of the data. Key factors include
 26 MSW combustion rate; fraction oxidized; missing data on MSW composition; average carbon content of MSW
 27 components; assumptions on the synthetic/biogenic carbon ratio; and combustion conditions affecting N₂O
 28 emissions. The highest levels of uncertainty surround the variables that are based on assumptions (e.g., percent of
 29 clothing and footwear composed of synthetic rubber); the lowest levels of uncertainty surround variables that were
 30 determined by quantitative measurements (e.g., combustion efficiency, carbon content of carbon black). Important
 31 sources of uncertainty are as follows:

- 32 • *MSW Combustion Rate.* A source of uncertainty affecting both fossil CO₂ and N₂O emissions is the
 33 estimate of the MSW combustion rate. The EPA (2000a, 2003, 2005a, 2006; Schneider 2007) estimates of
 34 materials generated, discarded, and combusted carry considerable uncertainty associated with the material
 35 flows methodology used to generate them. Similarly, the *BioCycle* (Glenn 1999, Goldstein and Matdes
 36 2000, Goldstein and Matdes 2001, Kaufman et al. 2004a, Kaufman et al. 2004b, Simmons et al. 2006)
 37 estimate of total waste combustion—used for the N₂O emissions estimate—is based on a survey of state
 38 officials, who use differing definitions of solid waste and who draw from a variety of sources of varying
 39 reliability and accuracy. The survey methodology changed significantly in 2003 and thus the results
 40 reported for 2002 are not directly comparable to the earlier results (Kaufman et al. 2004a, 2004b),
 41 introducing further uncertainty.
- 42 • *Fraction Oxidized.* Another source of uncertainty for the CO₂ emissions estimate is fraction oxidized.
 43 Municipal waste combustors vary considerably in their efficiency as a function of waste type, moisture
 44 content, combustion conditions, and other factors. A value of 98 percent was assumed for this analysis.
- 45 • *Missing Data on Municipal Solid Waste Composition.* Disposal rates have been interpolated when there is
 46 an incomplete interval within a time series. Where data are not available for years at the end of a time
 47 series, they are set equal to the most recent years for which estimates are available.
- 48 • *Average Carbon Contents.* Average carbon contents were applied to the mass of “Other” plastics
 49 combusted, synthetic rubber in tires and municipal solid waste, and synthetic fibers. These average values
 50 were estimated from the average carbon content of the known products recently produced. The actual

1 carbon content of the combusted waste may differ from this estimate depending on differences in the
 2 chemical formulation between the known and unspecified materials, and differences between the
 3 composition of the material disposed and that produced. For rubber, this uncertainty is probably small
 4 since the major elastomers' carbon contents range from 77 to 91 percent; for plastics, where carbon
 5 contents range from 29 to 92 percent, it may be more significant. Overall, this is a small source of
 6 uncertainty.

- 7 • *Synthetic/Biogenic Assumptions.* A portion of the fiber and rubber in municipal solid waste is biogenic in
 8 origin. Assumptions have been made concerning the allocation between synthetic and biogenic materials
 9 based primarily on expert judgment.
- 10 • *Combustion Conditions Affecting N₂O Emissions.* Because insufficient data exist to provide detailed
 11 estimates of N₂O emissions for individual combustion facilities, the estimates presented exhibit high
 12 uncertainty. The emission factor for N₂O from municipal solid waste combustion facilities used in the
 13 analysis is an average of default values used to estimate N₂O emissions from facilities worldwide (Johnke
 14 1999, UK: Environment Agency 1999, Yasuda 1993). These factors span an order of magnitude, reflecting
 15 considerable variability in the processes from site to site. Due to a lack of information on the control of
 16 N₂O emissions from MSW combustion facilities in the United States, the estimate of zero percent for N₂O
 17 emissions control removal efficiency also exhibits uncertainty.

18 Industrial Processes

19 Iron and Steel Production

20 The uncertainty upper and lower bounds of the CO₂ emission estimate for Iron and Steel Production were
 21 26 percent and -10 percent, respectively, at the 95 percent confidence interval. Simplifying assumptions were made
 22 concerning the composition of C anodes, (80 percent petroleum coke and 20 percent coal tar). For example, within
 23 the aluminum industry, the coal tar pitch content of anodes can vary from 15 percent in prebaked anodes to 24 to 28
 24 percent in Soderberg anode pastes (DOE 1997). An average value was assumed and applied to all carbon anodes
 25 utilized during aluminum and steel production. It was also assumed that the C contents of all pig iron and crude
 26 steel have carbon contents of 4 percent and 0.4 percent, respectively. The carbon content of pig iron can vary
 27 between 3 and 5 percent, while crude steel can have a carbon content of up to 2 percent, although it is typically less
 28 than 1 percent (IPCC 2000). Emissions vary depending on the specific technology used by each plant (Prebake or
 29 Soderberg). Emissions were estimated according to process and plant specific methodology outlined in the
 30 aluminum production section of this chapter. Based on expert elicitation, carbon anodes were assumed to be 20
 31 percent coal tar pitch for the whole time series (Kantamaneni 2005).

32 Ammonia Manufacture and Urea Application

33 The uncertainty upper and lower bounds of the emission estimate for Ammonia Manufacture and Urea
 34 Application were 8 percent and -8 percent, respectively, at the 95 percent confidence interval. The European
 35 Fertilizer Manufacturer's Association (EFMA) reported an emission factor range of 1.15 to 1.30 ton CO₂/ton NH₃,
 36 with 1.2 ton CO₂/ton NH₃ reported as a typical value. The actual emission factor depends upon the amount of air
 37 used in the ammonia production process, with 1.15 ton CO₂/ton NH₃ being the approximate stoichiometric minimum
 38 that is achievable for the conventional reforming process. By using natural gas consumption data for each ammonia
 39 plant, more accurate estimates of CO₂ emissions from ammonia production could be calculated. However, these
 40 consumption data are often considered confidential. Also, natural gas is consumed at ammonia plants both as a
 41 feedstock to the reforming process and for generating process heat and steam. Natural gas consumption data, if
 42 available, would need to be divided into feedstock use (non-energy) and process heat and steam (fuel) use, as CO₂
 43 emissions from fuel use and non-energy use are calculated separately.⁸⁶

⁸⁶ It appears that the IPCC emission factor for ammonia production of 1.5 ton CO₂ per ton ammonia may include both CO₂ emissions from the natural gas feedstock to the process and some CO₂ emissions from the natural gas used to generate process heat and steam for the process. Table 2-5, Ammonia Production Emission Factors, in Volume 3 of the *Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories Reference Manual* (IPCC 1997) includes two emission factors, one reported for Norway and one reported for Canada. The footnotes to the table indicate that the factor for Norway does not include natural gas used as fuel but that it is unclear whether the factor for Canada includes natural gas used as fuel. However, the factors

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

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

23 **Phosphoric Acid Production**

24 The uncertainty upper and lower bounds of the emissions estimate for Phosphoric Acid Production were 19
 25 percent and -18 percent, respectively, at the 95 percent confidence interval. Only one set of data from the Florida
 26 Institute of Phosphate Research (FIPR) was available for the composition of phosphate rock mined domestically and
 27 imported, and data for uncalcined phosphate rock mined in North Carolina and Idaho were unavailable. Inorganic
 28 carbon content (as CO₂) of phosphate rock could vary ±1 percent, resulting in a variation in CO₂ emissions of ±20
 29 percent.

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

38 **Aluminum Production**

39 The uncertainty upper and lower bounds of the PFCs emissions estimate for Aluminum Production were 7
 40 percent and -7 percent, respectively, at the 95 percent confidence interval. The uncertainties associated with three
 41 variables were estimated for each smelter: (1) the quantity of aluminum produced, (2) the anode effect minutes per
 42 cell day (which may be reported directly or calculated as the product of anode effect frequency and anode effect
 43 duration), and (3) the smelter- or technology-specific slope coefficient. All three types of data are assumed to be

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

1 characterized by a normal distribution. The uncertainty in aluminum production estimates was assumed to be 2
 2 percent for reported data (IPCC 2006). For reported anode effect frequency and duration data, the uncertainties
 3 were assumed to be 2 percent and 5 percent, respectively (Kantamaneni et al. 2001). For the three smelters that
 4 participated in the 2003 EPA-funded measurement study, the uncertainties in the smelter-specific CF_4 and C_2F_6
 5 slope coefficients were calculated to be 10 percent. For the two smelters with smelter-specific slope coefficients
 6 based on older studies, the uncertainty in the coefficients was assumed to be similar to that given by the IPCC
 7 guidance for technology-specific (Tier 2) slope coefficients. For the remaining 10 operating smelters, for which
 8 weighted average slope-factors were calculated based on technology-specific IPCC (2001) values, the uncertainty in
 9 the weighted average slope coefficients was based on information provided in IPCC (2001) for CWPB smelters, the
 10 technology type that makes up most of the production capacity of the 10 smelters. Consequently, the uncertainties
 11 assigned to the slope coefficients for CF_4 and C_2F_6 were 10 percent and 22 percent, respectively. (The uncertainty in
 12 CF_4 emissions is reported as 6 percent in IPCC (2001), but was increased to 10 percent in this analysis to better
 13 account for measurement uncertainty.) In general, where precise quantitative information was not available on the
 14 uncertainty of a parameter, an upper-bound value was used.

15 **Magnesium Production**

16 The uncertainty upper and lower bounds of the emissions estimate for Magnesium Production were 4
 17 percent and -4 percent, respectively, at the 95 percent confidence interval. An uncertainty of 5 percent was assigned
 18 to the data reported by each participant in the Magnesium Partnership. For non-reporting Partners, the uncertainty
 19 associated with the extrapolated emission factor was assumed to be 25 percent, while that associated with the
 20 extrapolated production was assumed to be 30 percent. For those industry processes that are not represented in the
 21 Partnership, such as permanent mold and wrought casting, SF_6 emissions were estimated using production and
 22 consumption statistics reported by USGS and estimated process-specific emission factors. The uncertainties
 23 associated with the emission factors and USGS-reported statistics were assumed to be 75 percent and 25 percent,
 24 respectively.

25 **Electric Transmission and Distribution**

26 The uncertainty upper and lower bounds of the emissions estimate for Electric Transmission and
 27 Distribution were 7 percent and -6 percent, respectively, at the 95 percent confidence interval. There are two
 28 sources of uncertainty associated with the regression equations used to estimate emissions in 2005 from non-
 29 partners: 1) uncertainty in the coefficients (as defined by the regression standard error estimate), and 2) the
 30 uncertainty in total transmission miles for non-partners. The uncertainty in the coefficients is estimated to be ± 21
 31 percent for small utilities and ± 41 percent for large utilities, while the uncertainty in the transmission miles is
 32 assumed to be 10 percent. For equipment manufacturers, the quantity of SF_6 charged into equipment by equipment
 33 manufacturers, which is projected from 2000 data from NEMA, is estimated to have an uncertainty of 65 percent,
 34 based on the variability of this quantity between 1996 and 2000. The manufacturers' SF_6 emissions rate has an
 35 uncertainty bounded by the proposed "actual" and "ideal" emission rates defined in O'Connell, et al. (2002). This
 36 implies that the uncertainty in the emission rate is also approximately 65 percent.

37 A Monte Carlo analysis was applied to estimate the overall uncertainty of the 2005 emission estimate for
 38 SF_6 from electrical transmission and distribution. For each defined parameter (i.e., equation coefficient,
 39 transmission mileage, and partner-reported and partner-estimated SF_6 emissions data for electric power systems; and
 40 SF_6 emission rate and statistics for manufacturers), random variables were selected from probability density
 41 functions, all assumed to have normal distributions about the mean.

42 **Agriculture Manure Management**

43 The uncertainty upper and lower bounds of the CH_4 emissions estimate for Manure Management were 20
 44 percent and -18 percent, respectively, at the 95 percent confidence interval. The primary factors that contribute to
 45 the uncertainty in emission estimates are a lack of information on the usage of various manure management systems
 46 in each regional location and the exact CH_4 generating characteristics of each type of manure management system.
 47 Because of significant shifts in the swine and dairy sectors toward larger farms, it is believed that increasing
 48 amounts of manure are being managed in liquid manure management systems. The existing estimates reflect these
 49 shifts in the weighted MCFs based on the 1992, 1997, and 2002 farm-size data. However, the assumption of a direct
 50 relationship between farm size and liquid system usage may not apply in all cases and may vary based on
 51 geographic location. In addition, the CH_4 generating characteristics of each manure management system type are

1 based on relatively few laboratory and field measurements, and may not match the diversity of conditions under
2 which manure is managed nationally.

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

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

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

25 **Rice Cultivation**

26 The uncertainty upper and lower bounds of the emissions estimate for Rice Cultivation were 170 percent
27 and -70 percent, respectively, at the 95 percent confidence interval. Uncertainty associated with primary rice-
28 cropped area for each state was assumed to range from 1 percent to 5 percent of the mean area based on expert
29 judgment. A normal distribution of uncertainty, truncated to avoid negative values, was assumed about the mean for
30 areas.

31 Ratooned area data, which are not compiled regularly, are an additional source of uncertainty. Although
32 ratooning accounts for only 5 to 10 percent of the total rice-cropped area, it is responsible for 15 to 30 percent of
33 total emissions. For states that have never reported any ratooning, it is assumed with complete certainty that no
34 ratooning occurred in 2005. For states that regularly report ratooning, uncertainty is estimated to be between 3
35 percent and 5 percent (based on expert judgment) and is assumed to have a normal distribution, truncated to avoid
36 negative values. For Arkansas, which reported ratooning in 1998 and 1999 only, a triangular distribution was
37 assumed, with a lower boundary of 0 percent ratooning and an upper boundary of 0.034 percent ratooning based on
38 the maximum ratooned area reported in 1998 and 1999.

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

45 Uncertainty associated with primary rice-cropped area for each state was assumed to range from 1 percent
46 to 5 percent of the mean area based on expert judgment. A normal distribution of uncertainty, truncated to avoid
47 negative values, was assumed about the mean for areas.

48 **Agricultural Soil Management**

49 An empirically-based uncertainty estimator was developed using a method described by Ogle et al. (2006)
50 to assess uncertainty in model structure associated with the algorithms and parameterization. The estimator was

1 based on a linear mixed-effect modeling analysis comparing N₂O emission estimates from eight agricultural
 2 experiments with 50 treatments. Although the dataset was relatively small, modeled emissions were significantly
 3 related to measurements with a p-value of less than 0.01. Random effects were included to capture the dependence
 4 in time series and data collected from the same experimental site, which were needed to estimate appropriate
 5 standard deviations for parameter coefficients. The structural uncertainty estimator accounted for bias and
 6 prediction error in the DAYCENT model results, as well as random error associated with fine-scale emission
 7 predictions in counties over a time series from 1990 to 2005. Note that the current application only addresses
 8 structural uncertainty in cropland estimates; further development will be needed to address these uncertainties in
 9 model estimates for grasslands. In general, DAYCENT tended to over-estimate emissions if the rates were above 6
 10 g N₂O m⁻² (Del Grosso et al., In prep)

11 For DAYCENT modeling, a Monte Carlo analysis was used to estimate uncertainty associated with input
 12 data coupled with the empirically-based estimator for addressing structural uncertainty in the model. The
 13 incorporation of stochastic features in the DAYCENT model application was a major change. Instead of estimating
 14 a single N₂O emission for each crop in a county, one hundred emission estimates were produced based on
 15 uncertainty in weather, soil characteristics, mineral N fertilization, and manure amendments. Furthermore, the
 16 uncertainty in model structure was quantified and used to adjust for biases in model results in addition to a measure
 17 of precision for N₂O emission estimates produced by the DAYCENT model.

18 The uncertainty for the Tier 1 calculations for minor crops and N inputs for grasslands that were not
 19 included in the DAYCENT simulations (see the section on Direct N₂O Emissions from Grassland Soils) was
 20 estimated using the simple error propagation method provided by IPCC (2000). In the previous inventory, the
 21 uncertainty in the Tier 1 method was assumed to be similar to the DAYCENT model application. However, this is
 22 unlikely because of different assumptions, input data, and uncertainties associated with default emission factors.
 23 Therefore, the uncertainty analysis for the Tier 1 method was revised with the goal of providing a more realistic
 24 confidence interval.

25 **Field Burning of Agricultural Residues**

26 The uncertainty upper and lower bounds of the CH₄ emissions estimate for Field Burning of Agricultural
 27 Residues were 13 percent and -13 percent, respectively, and of the N₂O emissions estimate were 12 percent and -11
 28 percent respectively, at the 95 percent confidence interval. The uncertainty in production for all crops considered
 29 here is estimated to be 5 percent, based on expert judgment. Residue/crop product ratios can vary among cultivars.
 30 Generic residue/crop product ratios, rather than ratios specific to the United States, have been used for all crops
 31 except sugarcane. An uncertainty of 10 percent was applied to the residue/crop product ratios for all crops. Based
 32 on the range given for measurements of soybean dry matter fraction (Strehler and Stützel 1987), residue dry matter
 33 contents were assigned an uncertainty of 3.1 percent for all crop types. Burning and combustion efficiencies were
 34 assigned an uncertainty of 5 percent based on expert judgment.

35 The N₂O emission ratio was estimated to have an uncertainty of 28.6 percent based on the range reported in
 36 IPCC/UNEP/OECD/IEA (1997). The uncertainty estimated for the CH₄ emission ratio was 40 percent based on the
 37 range of ratios reported in IPCC/UNEP/OECD/IEA (1997).

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

39 **Forest Land Remaining Forest Land**

40 **Changes in Forest Carbon Stocks**

41 The USDA Forest Service inventories are designed to be accurate within 3 percent at the 67 percent
 42 confidence level (one standard error) per 405,000 ha (1 million acres) of timberland (USDA Forest Service 2006c).
 43 For larger areas, the uncertainty in area is concomitantly smaller, and precision at plot levels is larger. An analysis
 44 of uncertainty in growing stock volume data for timber producing land in the Southeast by Phillips et al. (2000)
 45 found that nearly all of the uncertainty in their analysis was due to sampling rather than the regression equations
 46 used to estimate volume from tree height and diameter.

47 The uncertainty analyses for total net flux of forest C are consistent with the IPCC-recommended Tier 2
 48 methodology (IPCC 2003). Separate analyses are produced for forest ecosystem and HWP flux. The uncertainty
 49 estimates are from Monte Carlo simulations of the respective models and input data. Methods generally follow

1 those described in Heath and Smith (2000b), Smith and Heath (2000), and Skog et al. (2004). Briefly, uncertainties
 2 surrounding input data or model processes are quantified as probability density functions (PDFs), so that a series of
 3 sample values can be randomly selected from the distributions. Model simulations are repeated a large number of
 4 times to numerically simulate the effect of the random PDF selections on estimated total C flux. The separate
 5 results from the ecosystem and HWP simulations are pooled for total uncertainty.

6 Uncertainty about the latest reported net C flux in forest ecosystems is based on uncertainty in the two most
 7 recent state or sub-state C stocks, which are summed to the national total. Uncertainty analysis starts at the plot
 8 level since C stocks are based on plot-level estimates. Uncertainty about C density (Mg/ha) is defined for each of
 9 six C pools for each inventory plot. These are summed and multiplied by the uncertainty about plot-level expansion
 10 to generate PDF representation of uncertainty about total associated with each plot. These are summed to the state
 11 or sub-state total stocks, which are the basis for determining flux.

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

18 Non CO₂ Emissions from Forest Fires

19 The uncertainty upper and lower bounds of the CH₄ emissions estimate from Forest Fires were 92 percent
 20 and -71 percent, respectively, and of the N₂O emissions estimate 93 percent and -70 percent, respectively, at the 95
 21 percent confidence interval. To quantify the uncertainties for emissions from forest fires, a Monte Carlo (Tier 2)
 22 uncertainty analysis was performed using the information provided above. The uncertainty inputs are described in
 23 more detail in the section on non-CO₂ emissions from forest fires.

24 Uncertainty in forest area was estimated to be ± 0.24 percent for the 95 percent confidence interval (Heath
 25 2006a). This estimate was calculated based on FIA accuracy standards, which mandate that sampling error cannot
 26 exceed 3 percent error per 1 million acres of timberland (Heath 2006a). Uncertainty in average C density was
 27 estimated to be ± 0.4 percent for the lower 48 States and ± 1.2 percent for Alaska (Heath 2006a, 2006b). Uncertainty
 28 in the area of forest land considered to be under protection from fire and the total area considered to be under
 29 protection from fire were assumed to be 30 percent (IPCC 2003). Uncertainties in emission ratios were based on
 30 IPCC (2003) guidance to apply a 70 percent uncertainty range. Since the combustion factor (0.4) was a default
 31 IPCC (2003) value, the uncertainty range provided by IPCC (0.36 to 0.45) was assumed.

32 Direct N₂O fluxes from Forest Soils

33 The uncertainty upper and lower bounds of the emissions estimate for Direct N₂O Fluxes from Forest Soils
 34 were 211 percent and -59 percent, respectively, at the 95 percent confidence interval. The uncertainty range of the
 35 IPCC default emission factor for synthetic fertilizer applied to soil, according to IPCC (2006), ranges from 0.3 to 3
 36 percent. Because IPCC does not provide further information on whether this range represents the 95 percent
 37 confidence interval or the absolute minimum and maximum values, a triangular distribution was used to represent
 38 the uncertainty of the emission factor. The uncertainty in the area of forest land receiving fertilizer was
 39 conservatively estimated at ± 20 percent and in fertilization rates at ± 50 percent (Binkley 2004).

40 Cropland Remaining Cropland

41 The uncertainty upper and lower bounds of the emissions estimate for Cropland Remaining Cropland were
 42 38 percent and -43 percent, respectively, at the 95 percent confidence interval. Probability Distribution Functions
 43 (PDFs) for fertilizer were based on survey data for major U.S. crops, both irrigated and rainfed (ERS 1997; NASS
 44 2004, 1999, 1992; Grant and Krenz 1985). State-level PDFs were developed for each crop if a minimum of 15 data
 45 points existed for each of the two categories (irrigated and rainfed). Where data were insufficient at the state-level,
 46 PDFs were developed for multi-state Farm Production Regions. Uncertainty in manure applications for specific
 47 crops was incorporated in the analysis based on total manure available for use in each county, a weighted average
 48 application rate, and the crop-specific land area amended with manure (compiled from USDA data on animal
 49 numbers, manure production, storage practices, application rates and associated land areas receiving manure

1 amendments; see Edmonds et al. 2003). Together with the total area for each crop within a county, this yielded a
 2 probability that a given crop at a specific NRI point would either receive manure or not. A ratio of managed manure
 3 N production in each year of the inventory relative to 1997 was used to adjust the probability of an area receiving an
 4 amendment, under the assumption that greater or less managed manure N production would lead to a proportional
 5 change in amended area (see Tier 3 Methods Section for data sources on manure N production). Manure
 6 amendment areas were averaged across decades to produce the PDF for the Monte Carlo Analysis (i.e., 1980-1989,
 7 1990-2000). If soils were amended with manure, a reduction factor was applied to the N fertilization rate
 8 accounting for the interaction between fertilization and manure N amendments (i.e., producers often reduce mineral
 9 fertilization rates if applying manure). Reduction factors were randomly selected from probability distribution
 10 factors based on relationships between manure N application and fertilizer rates (ERS 1997). For tillage uncertainty,
 11 transition matrices were constructed from CTIC data to represent tillage changes for two time periods, combining
 12 the first two and the second two management blocks (i.e., 1980-1989, 1990-2000). A Monte Carlo analysis was
 13 conducted with 100 iterations in which inputs values were randomly drawn from the PDFs to simulate the soil C
 14 stocks for each NRI cluster of points (i.e., inventory points in the same county were grouped into clusters if they had
 15 the same land-use/management history and soil type) using the Century model.

16 An empirically-based uncertainty estimator was developed to assess uncertainty in model structure
 17 associated with the algorithms and parameterization. The estimator was based on a linear mixed effect modeling
 18 analysis comparing modeled soil C stocks with field measurements from 45 long-term agricultural experiments with
 19 over 800 treatments, representing a variety of tillage, cropping, and fertilizer management practices (Ogle et al.
 20 2006b). The final model included variables for organic matter amendments, N fertilizer rates, inclusion of
 21 hay/pasture in cropping rotations, use of no-till, setting-aside cropland from production and inclusion of bare fallow
 22 in the rotation. Each of these variables were found to be significant at a 95 percent probability level, and accounted
 23 for statistically significant biases in the modeled estimates from Century. For example, Century tended to under-
 24 estimate the influence of organic amendments on soil C storage, so a variable was added to adjust the estimate from
 25 Century. Random effects captured the dependence in time series and data collected from the same long-term
 26 experimental site, which were needed to estimate appropriate standard deviations for parameter coefficients. For
 27 each C stock estimate from the Monte Carlo analysis, the structural uncertainty estimator was applied to adjust the
 28 value accounting for bias and prediction error in the modeled values. The structural uncertainty estimator was
 29 applied by randomly drawing parameter coefficients from their joint probability distribution, in addition to random
 30 draws from PDFs representing the uncertainty due to site and site by year random effects. Finally, uncertainty in the
 31 land-use and management statistics from the NRI were incorporated into the analysis based on the sampling
 32 variance for the clusters of NRI points.

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

41 Uncertainties in Mineral Soil Carbon Stock Changes

42 **Tier 3 Approach**

43 The uncertainty analysis for the Tier 3 Century inventory had three components: 1) a Monte Carlo
 44 approach to address uncertainties in model inputs, 2) an empirically-based approach for quantifying uncertainty
 45 inherent in the structure of the Century model, and 3) scaling uncertainty associated with the NRI survey (i.e.,
 46 scaling from the individual NRI points to the entire U.S. agricultural land base using the expansion factors).

47 For the model input uncertainty, probability distribution functions (PDFs) were developed for fertilizer
 48 rates, manure application and tillage practices. An empirically-based uncertainty estimator was developed to assess
 49 uncertainty in model structure associated with the algorithms and parameterization. The estimator was based on a
 50 linear mixed effect modeling analysis comparing modeled soil C stocks with field measurements from 45 long-term
 51 agricultural experiments with over 800 treatments, representing a variety of tillage, cropping, and fertilizer
 52 management practices (Ogle et al. 2007). The final model included variables for organic matter amendments, N

1 fertilizer rates, inclusion of hay/pasture in cropping rotations, use of no-till, setting-aside cropland from production,
 2 and inclusion of bare fallow in the rotation. Each of these variables were found to be significant at a 0.05 alpha
 3 level, and accounted for statistically significant biases in modeled estimates from the Century model. Uncertainty in
 4 land-use and management statistics from the NRI were incorporated into the analysis based on the sampling
 5 variance for the clusters of NRI points.

6 **Tier 2 Approach**

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

10 **Additional Mineral C Stock Change Calculations**

11 A ± 50 percent uncertainty was assumed for additional adjustments to the mineral soil C stocks between
 12 1990 and 2005, accounting for additional C stock changes associated gains or losses in C sequestration after 1997
 13 due to changes in Conservation Reserve Program enrollment.

14 **Uncertainties in Organic Soil C Stock Changes**

15 Uncertainty in C emissions from organic soils was estimated in the same manner described for mineral soil
 16 using the Tier 2 method and Monte Carlo analysis. PDFs for emission factors were derived from a synthesis of 10
 17 studies, and combined with uncertainties in the NRI land use and management data for organic soils in the Monte
 18 Carlo analysis.

19 **Uncertainties in CO₂ Emissions from Liming**

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

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

40 **Land Converted to Cropland**

41 **Tier 2 Approach**

42 The uncertainty upper and lower bounds of the emissions estimate for Land Converted to Cropland were 29
 43 percent and -33 percent, respectively, at the 95 percent confidence interval. The uncertainty analysis for *Land*
 44 *Converted to Cropland* using the Tier 2 approach was based on the same method described for *Cropland Remaining*
 45 *Cropland*.

1 Uncertainties in Mineral and Organic Soil C Stock Changes

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

17 **Grassland Remaining Grassland**

18 Tier 2 Approach

19 The uncertainty upper and lower bounds of the emissions estimate for Grassland Remaining Grassland
 20 were 15 percent and -18 percent, respectively, at the 95 percent confidence interval. The uncertainty analysis for
 21 *Grassland Remaining Grassland* using the Tier 2 approach was based on the same method described for *Cropland*
 22 *Remaining Cropland*. The uncertainty in the inventory estimate of a 0.2 Tg CO₂ Eq. removal was 89 percent below
 23 the mean and 127 percent above the mean.

24 Additional Uncertainties in Mineral and Organic Soil C Stock Changes

25 The quantitative estimates of uncertainty presented above are missing several components. This section
 26 qualitatively describes these contributors to overall uncertainty. Minimal data exist on where and how much sewage
 27 sludge has been applied to U.S. agricultural land and the accounting of this activity appears to be much more
 28 difficult than the related-activity of using manure to amend agricultural soils. Consequently, there is considerable
 29 uncertainty in the application of sewage sludge, which is assumed to be applied to *Grassland Remaining Grassland*.
 30 However, some sludge may be applied to other agricultural land, but there is not sufficient information to further
 31 subdivide application among the agricultural land use/land-use change categories. Another limitation is that the
 32 current estimates may underestimate losses of C from organic soils because the *1997 National Resources Inventory*
 33 was not designed as a soil survey and organic soils frequently occur as relatively small inclusions within major soil
 34 types. Lastly, the IPCC Tier 2 methodology does not take into account changes in SOC stocks due to pre-1982 land
 35 use and land-use change.

36 **Land Converted to Grassland**

37 Tier 2 Approach

38 The uncertainty upper and lower bounds of the emissions estimate for Land Converted to Grassland were
 39 14 percent and -13 percent, respectively, at the 95 percent confidence interval. The uncertainty analysis for *Land*
 40 *Converted to Grassland* using the Tier 2 approach was based on the same method described for *Cropland*
 41 *Remaining Cropland*. See the Tier 2 section under minerals soils in the *Cropland Remaining Cropland* section for
 42 additional discussion.

43 Additional Uncertainties in Mineral and Organic Soil Carbon Stock Changes

44 The quantitative estimates of uncertainty presented above are missing several components. This section
 45 qualitatively describes these contributors to overall uncertainty. The agricultural soil C inventory has undergone
 46 several improvements during the past few years, such as the development of the Tier 3 inventory method to estimate

1 mineral soil C stock changes for the majority of U.S. grassland. However, some limitations remain in the analysis.
 2 First, the current agricultural soil C inventory includes some points designated as non-agricultural land-uses in the
 3 NRI if the points were categorized as agricultural land use in either 1992 or 1997, but were urban, water, or
 4 miscellaneous non-cropland (e.g., roads and barren areas) in another year. The impact on SOC storage that results
 5 from converting non-agricultural uses to grassland is not well-understood, and therefore, those points were not
 6 included in the calculations for mineral soils (emissions from organic soils, however, were computed for those
 7 points in the years that they were designated as grassland). Second, the current estimates may underestimate losses
 8 of C from organic soils because the *1997 National Resources Inventory* was not designed as a soil survey and
 9 organic soils frequently occur as relatively small inclusions within major soil types. Lastly, this IPCC Tier 2
 10 methodology does not take into account changes in SOC stocks due to pre-1982 land use and land-use change.

11 **Settlements Remaining Settlements**

12 **N₂O Fluxes from Settlement Soil**

13 The uncertainty upper and lower bounds of the emissions estimate for N₂O fluxes from Settlement Soil
 14 were 163 percent and -49 percent, respectively, at the 95 percent confidence interval. The uncertainty range for the
 15 IPCC's default emission factor for mineral and organic N additions applied to soil ranges from 0.3 to 3 percent
 16 (IPCC 2006). Because the IPCC does not provide further information on whether this range represents the 95
 17 percent confidence interval or the absolute minimum and maximum values, a triangular distribution was used to
 18 represent the uncertainty of the emission factor.

19 The uncertainty in the total amount of synthetic fertilizer N applied in the United States was estimated to be
 20 ± 3 percent (Terry 2005). The uncertainty in the amount of synthetic fertilizer N applied to settlement soils was
 21 conservatively estimated to range from 50 percent below to 20 percent above the estimated amount (Qian 2004).
 22 The uncertainty in the amounts of sewage sludge applied to non-agricultural lands and used in surface disposal was
 23 based on the uncertainty of the following data points, which were used to determine the amounts applied in 2005:
 24 (1) N content of sewage sludge; (2) total sludge applied in 2000; (3) wastewater existing flow in 1996 and 2000; and
 25 (4) the sewage sludge disposal practice distributions to non-agricultural land application and surface disposal.

- 26 (1) The value assumed for N content of sewage sludge could range from around 0.1 percent to around 17
 27 percent (McFarland 2001). Because information was not available on the distribution, a triangular
 28 distribution was assumed based on IPCC guidelines.
- 29 (2) The uncertainty in the total amount of sludge applied in 2000 was based on a comparison with similar data
 30 available from other publications, which were all within 3 percent of the value used in the Inventory
 31 calculations (BioCycle 2000, NRC 2002, WEF 1997, Bastian 1997). The distribution was estimated to be
 32 normal based on expert opinion (Boucher 2006).
- 33 (3) The uncertainty in the wastewater existing flow values for 1996 and 2000 was estimated at 0.0625 percent
 34 with a lognormal distribution (Plastino 2006).
 35

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

40 **Other**

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

42 The uncertainty upper and lower bounds of the emissions estimate for Yard Trimming and Food Scrap
 43 Stocks in Landfills were 94 percent and -40 percent, respectively, at the 95 percent confidence interval. The
 44 uncertainty ranges were assigned based on expert judgment and are assumed to be normally distributed around the
 45 inventory estimate, except for the values for decomposition rate, proportion of C stored, and moisture content for
 46 branches. The uncertainty ranges associated with these values are highlighted separately in this section.

47 The uncertainty range selected for input variables for the proportions of both grass and leaves in yard
 48 trimmings was 20 to 60 percent. The initial C content for grass, leaves, and food scraps (all expressed as

1 percentages in the calculations for the inventory) were plus or minus 10 percent. For the moisture content of
2 branches (where the inventory estimate is 10 percent), the uncertainty range was assumed to be 5 to 30 percent,
3 within a lognormal distribution.

4 The uncertainty ranges associated with the disposal of grass, leaves, branches, and food scraps were bound
5 at 50 percent to 150 percent of the inventory estimates. The half-lives of grass and food scraps were assumed to
6 range from 1 to 20 years, the half-life of leaves was assumed to range from 2 to 30, and the half life of branches was
7 assumed to range from 5 to 50 years. Finally, the proportion of C stored in grass, leaves, branches, and food scraps
8 was assumed to vary plus or minus 20 percent from the best estimate, with a uniform distribution.

9 **References**

10 EPA (2002) *Quality Assurance / Quality Control and Uncertainty Management Plan for the U.S. Greenhouse Gas*
11 *Inventory: Background on the U.S. Greenhouse Gas Inventory Process*, U.S. Environmental Protection Agency,
12 Office of Atmospheric Programs, Greenhouse Gas Inventory Program, Washington, D.C., EPA 430-R-02-007A,
13 June 2002.

14 IPCC/UNEP/OECD/IEA (1997) *Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories*, Paris:
15 Intergovernmental Panel on Climate Change, United Nations Environment Programme, Organization for Economic
16 Co-Operation and Development, International Energy Agency.

17 IPCC (2000) *Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories*,
18 Intergovernmental Panel on Climate Change, National Greenhouse Gas Inventories Programme, Montreal, IPCC-
19 XVI/Doc. 10 (1.IV.2000), May 2000.

20 IPCC/UNEP/OECD/IEA (2006) *2006 IPCC Guidelines for National Greenhouse Gas Inventories*, Paris:
21 Intergovernmental Panel on Climate Change, United Nations Environment Programme, Organization for Economic
22 Co-Operation and Development, International Energy Agency.

23

24

25

26