Chapter 8
Uncertainty Assessment for Quantifying Greenhouse Gas Sources and Sinks

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[1] All authors of Chapters 3, 4, 5, and 6 provided strategic input in the parameters in the uncertainty chapter.

Acronyms, Chemical Formulae, and Units

CONUS STATSGO	Continental United States Soil Geographic Database
DBH	Diameter at breast height
DNDC	DeNitrification-DeComposition
EPA	U.S. Environmental Protection Agency
ERS	USDA Economic Research Service
FOFEM	First Order Fire Effects Model
FVS	Forest Vegetation Simulator
GHG	Greenhouse gas
IPCC	Intergovernmental Panel on Climate Change
NADP	National Atmospheric Deposition Program
NARR	North American Regional Reanalysis
NASS	USDA National Agricultural Statistics Service
NCEP	National Centers for Environmental Prediction
NLCD	National Land Cover Database
NOAA	National Oceanic and Atmospheric Administration
NRCS	USDA Natural Resources Conservation Service
NRI	National Resource Inventory
PDF	Probability density function
PRISM	Parameter-elevation Regressions on Independent Slopes Model
SOC	Soil organic carbon
SSURGO	Soil Survey Geographic
USDA	U.S. Department of Agriculture

8 Uncertainty Assessment for Quantifying Greenhouse Gas Sources and Sinks

Quantifying the uncertainty of greenhouse gas (GHG) emissions and reductions from agriculture and forestry practices is an important aspect of decision-making for farmers, ranchers and forest landowners as the uncertainty range for each GHG estimate communicates our level of confidence that the estimate reflects the actual balance of GHG exchange between the biosphere and the atmosphere. In particular, a farm, ranch, or forest landowner may be more inclined to invest in management practices that reduce net GHG emissions if the uncertainty range for an estimate is low, meaning that higher confidence in the estimates exists. This chapter presents the approach for accounting for the uncertainty in the estimated net emissions based on the methods presented in this report.[2] A Monte Carlo approach was selected as the method for estimating the uncertainty around the outputs from the methodologies in this report as it is currently the most comprehensive, sound method available to assess the uncertainty at the entity scale. Limitations and data gaps exist; however, as new data become available the method can be improved over time. Implementation of a Monte Carlo analysis is complicated and requires the use of a statistical tool to produce a probability density function (PDF)[3] around the GHG emissions estimate.[4] From the PDF, the uncertainty estimate can be derived and reported.

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[2] The IPCC Good Practice Guidance (IPCC, 2000) recommends two approaches—Tier 1 and Tier 2—for developing quantitative estimates of uncertainty for emissions estimates for source categories. The Tier 1 method uses error propagation equations. These equations combine the uncertainty associated with the activity data and the uncertainty associated with the emission (or other) factors. This approach is appropriate where emissions (or removals) are estimated as the product of activity data and an emission factor or as the sum of individual sub-source category values. The Tier 2 method utilizes the Monte Carlo Stochastic Simulation technique. Using this technique, an estimate of emission (or removal) for a particular source category is generated many times via an uncertainty model, resulting in an approximate PDF for the estimate. Where sufficient and reliable uncertainty data for the input variables are available, the Tier 2 method is the preferred option.

[3] The integral of a PDF over a given interval of values is the probability for a random variable to take on some value in the interval. That is, the PDF is a function giving probability "densities" and its integral gives probabilities. A narrower PDF for an estimate indicates smaller variance around the central/most likely value, i.e., a higher probability of the value to be closer to the central/most likely value. The uncertainty for such an estimate is lower.

[4] Given the complexity of Monte Carlo analysis and the necessity for a tool, the approach presented here is not intended for development by a landowner, rather it is intended for use in developing a tool that a landowner would use to assess uncertainty estimates.

Monte Carlo Analysis for Assessing Uncertainty

- In the Monte Carlo method, uncertain inputs (parameters and other data) and uncertain model structure are described via PDFs. By randomly selecting from each of these PDFs, and running the selected inputs through the selected model, an uncertainty model output is obtained. Combining these model outputs across many random selections leads to an approximate PDF describing uncertainty in the model output, reflecting known sources of uncertainty in the inputs and model structure.
- A tool is needed to run a Monte Carlo analysis to assess the uncertainty for model outputs. Farmers and landowners are not expected to perform a Monte Carlo analysis on their own.
- A centralized database is needed to store information on the known uncertainties associated with the activity and emission factor data for each emissions source. This report presents readily available data that can form the initial foundation for such a database.

Uncertainty in GHG emissions estimation arises because of unknown or incompletely known factors associated with:

- Parameters – Due to limitations associated with available input data (e.g., activity data and emission factors).
- Sampling methods – Due to either measurement errors during sample collection or potential variations in values obtained from sampling (i.e., when the chosen sample is not fully representative of the entire population).
- Large datasets – Due to measurements errors during data collection, and variations in dataset values for a given set of conditions.
- Models – Due to approximation errors and estimation errors. Approximation error arises because the model is a simplification of the real system, while estimation error arises because the theoretical model is fitted using limited data.
- Concepts – This is closely related to model approximation error and occurs because the conceptual scope does not capture the actual/real scope thus creating a bias. For an entity, this conceptualization uncertainty may be relatively small.

The approach to address uncertainty does not address conceptual uncertainty because it is expected to be small and difficult to quantify. This chapter addresses parameter uncertainty, sampling uncertainty, large dataset uncertainty, and model approximation uncertainty. Where data are currently unavailable or incomplete for establishing PDF's and estimating uncertainty, the authors provide expert judgment and/or a qualitative description of uncertainty in the interests of making the GHG management methods as transparent and complete as possible. In the future, new data can be used to refine and improve the estimation of uncertainty.

In this chapter, Section 8.1 includes the components and inputs to an entity-scale Monte Carlo uncertainty assessment, and Section 8.2 highlights research gaps.

8.1 Components and Inputs to an Entity-Scale Monte Carlo Uncertainty Assessment

To conduct a Monte Carlo uncertainty analysis for each of the GHG quantification methods and resulting net GHG emissions, information is required about the uncertainty associated with: (1) the input variables (i.e., parameters); (2) sampling methods used to obtain data; (3) existing large datasets used as data sources; and (4) external models used. Ideally, this information would consist of specific PDFs (e.g., normal, triangular, uniform, beta). Alternatively, the uncertainty might be described with summary statistics, such as lower and upper bounds for intervals with specified confidence, minimum, maximum, mean, and standard deviation. This summary information forms the basis for constructing approximate PDFs for the Monte Carlo method. Repeated selections are made from these PDFs. These selections represent the range of possible outcomes from each PDF. Random sampling from the PDFs will ensure such representativeness.[5] By randomly selecting from each of these PDFs and running the selected inputs through the model, a range of outputs is obtained. Combining these model outputs across many random selections leads to an output PDF that can be used to describe uncertainty in the estimate, accounting for known sources of uncertainty in the inputs and model structure.

This section presents readily available information on each of the key components of uncertainty. In summary, although information on all the components are described here, the Monte Carlo method for assessing net GHG emissions uncertainty relies most heavily on parameter uncertainty, for which the best PDF data and information are available. Other components of uncertainty are discussed, including limitations such as characterizing the uncertainty associated with other components. These components can be readily improved or refined in the uncertainty analysis as additional information becomes available. Overall uncertainty is typically greater than any particular uncertainty component (e.g., sampling, large data sets, models) and can be readily improved or refined as additional information becomes available. As the uncertainty associated with the other components is addressed, the uncertainty will increase (i.e., addressing only parameter uncertainty sets a lower bound for overall uncertainty). Therefore, the quantification of parameter uncertainty sets a lower bound for overall uncertainty.

8.1.1 Parameter Uncertainty

Parameter uncertainty is the primary source of uncertainty in the net GHG estimates. This section presents readily available information on parameters used to estimate net GHG emissions from animal production systems, croplands and grazing lands, and forestry GHG estimation methods. For each input variable, readily available information was collected on the probability distribution; variance; standard deviation; expected mean, median, and mode; most likely value; minimum; maximum; relative uncertainty absolute values; confidence interval; and data sources. The information was collected primarily from published literature, such as the Intergovernmental Panel on Climate Change (IPCC) Guidelines (2006), the U.S. National GHG Inventory Report (U.S. EPA, 2012), and peer-reviewed journals. In the absence of published data, default factors are indicated based on expert judgment obtained from the Working Groups. The information obtained to date is presented in Appendix 8-B.[6, 7, 8]

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[5] An alternative approach to selecting from the PDFs is *Latin hypercube sampling* (McKay et al., 1979; Helton and Davis, 2003).

[6] Uncertainty for the forestry sector is mainly driven by modeling and sampling uncertainty; consequently, only a few parameters have been listed in Appendix 8-B.

[7] The Wetlands Chapter methods suggest use of the FVS and DNDC models in combination with the lookup tables for dominant shrub and grassland vegetation types found in Chapter 3, for estimating biomass carbon, soil carbon, N_2O, and CH_4 emissions and removals in wetlands. Descriptions of these models and the uncertainty associated with the look-up tables are included in the Uncertainty Assessment (Chapter 8).

[8] An uncertainty assessment was not completed for the Land-use Change Chapter methods (i.e., annual change in carbon stocks in dead wood and litter due to land conversion, change in soil organic carbon stocks for mineral soils) as they are based upon IPCC 2006 Guidance and no U.S. specific customizations were made to these methods. Uncertainty assessments for each land-use and transition into or out of a land-use category

In order to make the uncertainty estimation process feasible and consistent at the entity scale for use by an entity or landowner, a tool will be needed that provides the following uncertainty information for input variables:

- PDFs or distributions – Default
- Emission factors – Default
- Activity data – Default, but customizable

With default uncertainty information available, it is feasible to quantify parameter uncertainty via PDFs and to combine the uncertainty via Monte Carlo methods. These PDFs are often relatively crude, relying on default values and conservative expert judgment. Options to improve the PDFs (i.e., improve parameter uncertainty quantification) are to: (1) develop a method to help elicit and refine these uncertainty distributions at an entity scale; and (2) conduct new research to better understand the key parameters identified in this report and to quantify their uncertainties.[9]

The uncertainty associated with the various inputs to the GHG estimation equation or models are combined to estimate overall uncertainty at the entity level for: (1) each source category emission estimate; and (2) total emission estimate arrived at by aggregating each source category's estimate. Although most inputs within a category and across categories are independent, certain variables might be the same, similar, or highly co-related, and will need to be accounted for appropriately in the uncertainty analysis.

8.1.2 Sampling Method Uncertainty

Some sampling methods (i.e., field measurements) will be conducted to support the estimation of emissions using the GHG quantification methods. For example, for the forestry sector, conducting field measurements on sampling plots for large forest and on urban forests is used to determine aggregate forest characteristics (e.g., tree cover). Additionally, some large datasets and external models that the methods use also utilize data that were obtained from a variety of outside sampling methods. For example, forest inventory data used in the forest vegetation simulator (FVS) model and the average carbon sequestration rates used in the i-Tree model use data obtained through sampling methods. In addition, there are instances in these external models and large datasets where the variation in measurements obtained from the sampling methods is not taken into account, but they can impact uncertainty.

If forest stand sampling is conducted at an entity level using a formal probability sampling design, then unbiased estimates of sampling error variance can be computed via standard techniques from the field of survey statistics. The exact form of the variance estimate depends on the particular design used for the stand sampling. Though additional uncertainties arise from the actual measurement protocols used in the field, the sampling error variance is a major part of the sampling uncertainty. A currently feasible approach to incorporating information on sampling error variances into the uncertainty analysis is to model the sampling error PDF as a normal distribution with zero as its mean and the estimated sampling error variance as its variance.[10] This section

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are contained in the associated land-use category chapter of the 2006 IPCC Guidelines. http://www.ipcc-nggip.iges.or.jp/public/2006gl/vol4.html

[9] A tool could provide an option to use pre-defined values such as those provided in Appendix 8-B or user (i.e., landowner) supplied values to define PDFs.

[10] Similarly, estimates derived from existing surveys and tools such as Forest Inventory Data Online in the Forest Inventory and Analysis National Program or the USDA Natural Resources Inventory (NRI) Summary Reports have associated sampling error variances from well-established statistical procedures. In these cases,

provides the sampling methods and their potential sources of uncertainty. However, given the complexity in incorporating information on uncertainty for sampling data in the Monte Carlo uncertainty assessment, a tool will be needed to quantify the impact of sampling uncertainty on the estimate of net GHG emissions.[11]

8.1.2.1 Forest Stand Sampling with Plots for Use with the Forest Vegetation Simulator Model

The FVS model is a family of forest growth simulation model variants. FVS estimates forest carbon stocks based on sample data parameters (e.g., the diameter, height, species, and canopy density of trees from representative sample plots established across the forest). For sampling purposes, a number of plots are established within a forest that can serve as a representative sample of the entire forest. As the variance in forest types increases, the number of plots will increase. The size and number of plots should be determined based on the variance in carbon stocks between plots. Complete forest estimates have sampling uncertainty, but larger and more numerous plots help to create a more representative sample and lower the uncertainty associated with carbon stock estimates produced by FVS. Both permanent and temporary plots can be used in sampling; however, a larger uncertainty is associated with temporary plots. Note that the use of permanent plots is recommended in this report. This type of sampling methodology is commonly referred to as a forest inventory.

Once plots have been defined, all trees above a certain diameter at breast height (DBH) (commonly 2.5 cm. or 1 in.) are measured and recorded.[12] DBH, height, and a variety of other measurements are recorded, but DBH alone is sufficient for use with FVS. FVS uses DBH and available information to develop carbon density estimates for the entire forest. If provided, FVS models growth estimates for future years based on average growth rates and variables such as thinning.[13] Selecting plots to represent entire forests means FVS outputs are subject to the sampling method uncertainty. However, uncertainty in the FVS outputs can be lowered (i.e., more representative carbon stock estimates can be obtained) by collecting more detailed tree data beyond DBH as well as ensuring that sample plots are large and numerous enough to cover the variety of tree growth settings in a forest.

The forest inventory data recommended for use with FVS in this report is based on the sampling methods described in the U.S. Department of Agriculture (USDA) Measurement Guidelines for the Sequestration of Carbon (Pearson et al., 2007). These guidelines also describe the potential uncertainty associated with such sampling methods. According to these measurement guidelines, a reasonable estimate of the net change in carbon stocks would be within 10 percent of the true value of the mean at the 95 percent confidence level that can be achieved by having a sufficiently large sample size (Pearson et al., 2007). Different carbon pools in a forest can have different variances; however, focusing on the standing live tree component for forestry activities can capture most of the total variance.

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it may be feasible to use these estimated variances fairly directly. In other cases, it might be necessary to consider small area estimation techniques to describe uncertainty as large-scale survey data are downscaled to entity levels. Describing this type of uncertainty would require building statistical models for complex survey data and, hence, is not addressed in this report as additional research is required.

[11] For example, in addressing uncertainty in growth of forest biomass, algorithms to account for nonlinear growth patterns will be needed.

[12] Under common stand exams, even trees less than 2.5 cm or 1 in can be measured, but these trees are often considered to be part of the understory (e.g., by FIA).

[13] Other variables, such as fertilization, only apply to a few FVS variants.

The forest inventory data that is used for modeling the changes in forest stands is likely the largest source of parameter uncertainty for the inputs and assumptions used in the FVS model; in addition, there are many components in the FVS model where variation in measurements for this data is not taken into account. For example, the potential error distribution from month to month in carbon storage associated with leaves and foliage is not accounted for in the FVS model.

In a research paper on obtaining sampling uncertainty in FVS, experts note the challenge of reporting distributions of model inputs that include sampling uncertainty in FVS projections (Gregg and Hummel, 2002). They state in their introduction that, "it hasn't been possible to compute the effects of sampling uncertainty because classical statistical methods are not available to make inferences about FVS projections. A variance estimator is not available for the results of simulation."

As provided in Appendix 8-A, the FVS model provides quantitative information on the range and variability of sampling data. This FVS application, called FVSBoot, uses "bootstraps" to determine fluctuation in estimate outcomes (Gregg and Hummel, 2002) (i.e., allows modeler to empirically approximate the sampling distribution of any statistic/FVS attribute for which the modeler wants to make inferences).

Bootstrap sampling[14] using the FVSBoot program can be used to empirically approximate the sampling distribution of statistics for which inferences are to be drawn. New samples of stand conditions can be generated by sampling the original plots with replacement to create a bootstrap sample. A bootstrap mean can be generated from the bootstrap sample. Repeating this process multiple times will generate a Monte Carlo approximation of the distribution of bootstrap means. The standard deviation of this approximation will be an estimation of the true standard deviation for the entire population. FVSBoot does not cover all potential sources of variation but it can give a measure of important components of uncertainty in FVS model projections. While the FVSBoot program can be used to determine the sampling uncertainty in FVS, it was not developed originally to produce an overall uncertainty estimate for FVS outputs. However, FVSBoot has been used for sensitivity analysis of some FVS outputs (Hummel et al., 2013). A tool would be needed to facilitate developing an estimate of the uncertainty based on a combination of the results from the FVSBoot program and underlying equations used in the FVS model.

8.1.2.2 Urban Tree Population Sampling for Use with the Field Data Method Using the i-Tree Eco Model

The i-Tree Eco model estimates urban forest carbon stocks and gross and net annual carbon sequestration based on sample data parameters (e.g., the tree species, diameter, height, dieback, and crown light exposure) with a calculated level of precision. As desired by the landowner, all trees can be measured or a random distribution of field plots can be measured to quantify the urban tree population. Larger and more numerous plots help to create a more representative sample and lower the uncertainty associated with the sampling. The i-Tree Eco model uses the sample data parameters and forest-derived allometric equations to estimate carbon values. The model also estimates the standard error of the estimated carbon value, which is based on the sampling uncertainty, rather than the error of estimation from applying the allometric equations. Estimation error is unknown and likely larger than the reported sampling error. A Monte Carlo

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[14] Bootstrapping is the process of estimating variance by repeated random sampling with replacement of an existing data set. For example, to determine the probability distribution of average DBH for a sample of 100 trees, resamples of the data set of 100 trees can be taken to approximate the variance.

analysis tool could use the standard error of the estimated carbon value to evaluate the uncertainty associated with an entity's total net GHG emissions.

8.1.2.3 Sampling and DAYCENT for Estimating Biomass Carbon in Grazing Land and Agroforestry Systems

Sampling uncertainty will exist when estimating biomass carbon using the method provided in Chapter 3. For example, peak forage estimates for grazing lands can be sampled using the biomass clipping method.[15] This method is destructive with the removal of forage samples from the field. This method has been shown to produce estimates with low uncertainty (Lauenroth et al., 2006; Byrne et al., 2011). Non-destructive methods can also be used including the comparative yield method for rangelands,[16] or the robel pole method on rangelands or pastures (Harmoney et al., 1997; Vermeire et al., 2002). The biomass clipping method and comparative yield methods have less uncertainty than the robel pole or visual obstruction method. Destructive sampling methods, however, are more time and labor intensive. Uncertainty associated with the robel pole method was assessed in the Black Hills of South Dakota in a study by Uresk and Benzon (2007). The authors compared destructive (clipping) methods for estimating biomass and the robel pole method. They found there was a linear relationship between the two methods and the standard error of the robel pole estimate for a single mean was 373 kg ha^{-1}. The study further recommends that a minimum of three transects be sampled for monitoring areas less than 259 ha to be within 20 percent of the mean and 80 percent confident (Uresk and Benzon, 2007). In a similar study by Vermeire et al., (2002), a single visual obstruction model (i.e., robel pole method) effectively estimated herbage standing crop across range types and produced a coefficient of determination of 0.93. Any sampling that is done, whether destructive or non-destructive, should occur at locations that are representative of the land parcel. If sampling the forage is not feasible, default forage production values are provided by the USDA Natural Resources Conservation Service (USDA-NRCS) in Ecological Site Descriptions.[17] The sampling uncertainty will depend on the method used to collect the sample and should be provided by the farmer or landowner.

8.1.3 Large Dataset Uncertainty

Information from several large datasets will be used with the GHG quantification methods to estimate emissions from the animal agriculture, cropland and grazing land, and forestry sectors. Large datasets can be considered any grouping of data points that cover a wide time-series and/or level of reported variables. These data sets include multiple data layers, GIS data, databases, and other such reporting catalogues.

The large datasets to be used include the Smith et al. (2006, also known as GTR-NE-343), Forest Inventory and Analysis, FVS, Daymet, and the dataset from the i-Tree model. These datasets provide values for estimation equation and model inputs. These inputs include region- and species-specific tree growth rates, land and tree cover, inferred and observed meteorological data, soil type and distribution, ammonia content, and historical climate data for the North American continent. These data will be used to inform the carbon densities of small forest holdings, coverage of urban trees, direct and indirect N_2O emissions, soil pH, organic matter values, ambient air ammonia concentrations, and daily air temperature and velocity.

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[15] See Section 15, "Standing Biomass" (USDA NRCS, 2011b).

[16] See Section 13, "Dry Weight Rank" (USDA NRCS, 2011b).

[17] See USDA NRCS (2011a).

This section includes a description of the large datasets used for estimating forestry and agroforestry sector carbon stocks and stock changes, GHG emissions and removals from wetlands, soil carbon stocks, and ammonia emissions. The section also provides uncertainty information obtained from the dataset developers and an approach to incorporating uncertainty associated with these datasets into the overall uncertainty analysis.

Many of the large datasets are complex and cover multiple parameters. In some instances uncertainty information is available for some variables but not for others, making it difficult to assess the uncertainty of the entire dataset. Table 8-1 below summarizes the uncertainty documentation available for each large dataset used. The majority of datasets did not have publically available documentation characterizing the associated uncertainty.

Table 8-1: Availability of Uncertainty Information for Large Datasets

Dataset Name	Dataset Abbreviation	Availability of Uncertainty Documentation
Methods for Calculating Forest Ecosystem and Harvested Carbon with Standard Estimates for Forest Types of the United States (Smith et al., 2006)	GTR-NE-343	No published quantification of uncertainty. Standard errors available for carbon density for live and standing dead trees at the 50th and 99th percentile of volume.
National Land Cover Database	NLCD	No published quantitative uncertainty information found. Authors only provide information on contributing factors.
Daily Surface Weather and Climatological Summaries	Daymet	No published quantitative uncertainty information found.
Contiguous United States Soil Geographic Database	CONUS STATSGO	No published quantitative uncertainty information found.
Soil Survey Geographic Database	SSURGO	No published quantitative uncertainty information found.
Ammonia Monitoring Network	AMoN	No published quantitative uncertainty information found.
Parameter-Elevation Regressions on Independent Slopes Model	PRISM	No published quantitative uncertainty information found.
North American Regional Reanalysis	NARR	Regional-scale accuracy and bias reported by Mesinger (2006).
Natural Resources Inventory	NRI	Data are collected using a two-stage sampling process. Statistically valid uncertainties in management practices are computable at Major Land Resource Areas or State level.
National Agricultural Statistics Service Agricultural Census	NASS-agricultural census	No published quantitative uncertainty information found.
National Agricultural Statistics Service – Cropland Data Layer	NASS – Cropland Data Layer	NASS provides accuracy information and error matrices (total accuracy, errors of omission and co-mission), but not on an annual basis for crops and States.
Economic Research Service Cropping Practices Survey	ERS-CPS	No published quantitative uncertainty information found.
Economic Resource Service Agricultural Resource Management Survey	ERS-ARMS	No published quantitative uncertainty information found.

Dataset Name	Dataset Abbreviation	Availability of Uncertainty Documentation
National Climatic Data Center of the National Oceanic and Atmospheric Administration	NCDC (NOAA)	NCDC provides values that describe the range of the uncertainty, or simply "range," of each month's, season's, or year's global temperature anomaly. These values are provided as plus/minus values.
Modern-Era Retrospective Analysis for Research and Applications	MERRA (NASA)	No published quantitative uncertainty information found.
National Centers for Environmental Prediction	NCEP (NOAA)	No published quantitative uncertainty information found.
National Atmospheric Deposition Program	NADP	Regional-scale uncertainty was assessed in Dennis et al. (2011).

8.1.3.1 GTR-NE-343 Carbon Density Values

Estimates of carbon stocks and stock changes from the report, “Methods for Calculating Forest Ecosystem and Harvested Carbon with Standard Estimates for Forest Types of the United States” (Smith et al., 2006) (USDA Forest Service, General Technical Report NE-343), are based on regional averages and reflect the current best available data. However, according to GTR-NE-343, “quantitative expressions of uncertainty are not available for most data summaries, coefficients, or model results presented in the [GTR-NE-343] tables.” GTR-NE-343 lookup tables include some information about the confidence intervals for live and standing dead tree carbon densities at two different average volumes (see Table 20 of GTR-NE-343), but it does not prescribe a method for applying these summary uncertainty statistics to stand level carbon stock estimates.

The uncertainty associated with these reported regional average carbon stock values is likely higher as these values are applied to smaller-scale projects rather than regions. Sampling uncertainty associated with the regional averages, that are based on data summaries or models, can influence estimates for specific projects. These projects are generally small subsets of a region. Yet, variability within a region for values in a dataset will likely have a much greater influence on uncertainty than the actual sampling uncertainty associated with collecting regional values (Smith et al., 2006).

Once the user finds the table in GTR-NE-343 that describes the forest’s species mix and region, the user can use the age (or volume) of the forest stand (which is also collected with a high level of uncertainty) to find out the metric tons of carbon per acre density value for live tree carbon, down deadwood, organic soil carbon, and other categories. The uncertainty information is given as 95 percent confidence intervals for the carbon density of live and standing dead trees, at two different growing stock volumes—the 50th percentile and the 99th percentile. These confidence intervals are given for each forest type and region. To use this information in an uncertainty analysis requires extrapolation to other growing stock volumes, which requires modeling the relationship between growing stock volume and variation in carbon density. While these tables are simple and easy to use, the uncertainty of results obtained by using representative average values may be high relative to other techniques that use site- or project-specific data. Additional research is needed to include this uncertainty into a Monte Carlo analysis framework.

8.1.3.2 National Land Cover Database Map

The National Land Cover Database (NLCD) Map is the product of the Multi-Resolution Land Characterization partnership, a consortium of Federal agencies including the U.S. Geological Survey, Environmental Protection Agency (EPA), National Oceanic and Atmospheric Administration (NOAA), and the USDA Forest Service that are continuously developing digital land cover data. This association has successfully provided land cover data for the lower 48 States, Hawaii, Alaska, and Puerto Rico from decadal Landsat satellite imagery and other associated imaging datasets. The database provides Landsat-based, 30-meter resolution, land coverage characteristics including thematic class (e.g., urban, agriculture, and forest), percent impervious surface, and percent tree canopy cover.

Regarding uncertainty, the NLCD map documentation indicates, "Unfortunately, there is no readily available reference dataset with which to compare the inventory to generate accuracy statistics. Reference data have to be specifically generated through manual interpretation of remote sensing data for a sample of locations, as has been done for accuracy assessment of land cover maps. In lieu of such an approach, which is outside the scope of this study, the best that can be done currently to describe the uncertainty of the inventory data is to identify the known conditions that contribute to it" (National Land Cover Database, 2008).

8.1.3.3 Continental United States Soil Geographic Database

The Continental United States Soil Geographic Database (CONUS STATSGO) is a digital general soil association map that has been developed by the National Cooperative Soil Survey and distributed by the USDA NRCS. It consists of broad based inventory of soils and non-soil areas that occur in a repeatable pattern on the landscape and that can be cartographically shown at scale and mapped. No information is readily available on the uncertainty associated with this dataset.

8.1.3.4 Soil Survey Geographic Database

The Soil Survey Geographic (SSURGO) database has been developed by the National Geospatial Management Center, formerly the National Cartography and Geospatial Center. The SSURGO database depicts information about the kinds of soils and distribution of soils on the landscape. This dataset is a digital soil survey and generally is the most detailed level of soil geographic data available. Uncertainty information was not readily available for this database beyond the disclaimer that the accuracy of data points 'met national map accuracy standards.'

8.1.3.5 Ammonia Monitoring Network

The Ammonia Monitoring Network is part of the National Atmospheric Deposition Program (NADP), and was originally initiated by the U.S. State Agricultural Experiment Stations. The dataset provides consistent, long term record of ammonia gas concentrations in the United States, drawing from 50 monitoring sites across 37 states in total. Uncertainty was not directly addressed in the dataset materials, aside from the disclaimer that the NADP's Central Analytical Laboratory (CAL) analyzes, quality assures, and provides the analytical data to the NADP (2011).

8.1.3.6 Parameter-elevation Regressions on Independent Slopes Model

The Parameter-elevation Regressions on Independent Slopes Model (PRISM) is a climate mapping system developed by the PRISM Climate Group. PRISM is a knowledge-based system that uses point measurements of precipitation, temperature, and other climatic factors to produce continuous, digital grid estimates of monthly, yearly, and event-based climatic parameters. No information is readily available on the uncertainty associated with this dataset.

8.1.3.7 Daymet Weather Dataset

Daymet is a weather model developed by Oak Ridge National Laboratory that provides interpolations extracted from daily meteorological observations onto a gridded dataset where no such observations are present. Daymet provides output parameters including temperature, precipitation, humidity, solar radiation, and snow water equivalent. The Daymet dataset is based on the spatial convolution of a truncated Gaussian weighting filter with the set of station locations. Sensitivity to the typical heterogeneous distribution of stations in complex terrain is accomplished with an iterative station density algorithm. The weather datasets are produced as outputs from the Daymet model run. This dataset is used as an input for estimating GHG emissions from croplands and grazing lands, and ammonia emissions from manure management. No information is readily available on uncertainty associated with this dataset.

8.1.3.8 North American Regional Reanalysis Weather Dataset

The DAYCENT model simulations use the North American Regional Reanalysis (NARR) data product for daily temperature and precipitation. The NARR dataset was chosen because it provides full, gap-filled coverage for the conterminous U.S. and is maintained and updated regularly. As described by Mesinger (2006), "The National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) is a long-term, dynamically consistent, high-resolution, high-frequency, atmospheric and land surface hydrology dataset for the North American domain. It covers the 25-year period 1979–2003, and is being continued in near-real time as the Regional Climate Data Assimilation System, R-CDAS. Essential components of the system used to generate NARR are the lateral boundaries from and the data used for the NCEP/DOE Global Reanalysis, the NCEP Eta Model and its Data Assimilation System, a recent version of the NOAA land surface model, and the use of numerous data sets additional to or improved compared to those of the Global Reanalyses. In particular, NARR has successfully assimilated high quality and detailed precipitation observations into the atmospheric analysis. Consequently, the forcing to the land surface model component of the system is more accurate than in previous reanalyses, so that NARR provides a much improved analysis of land hydrology and land-atmosphere interaction." No quantitative information is readily available on uncertainty associated with this dataset.

8.1.3.9 DAYCENT Land Management Data Sets

Data on past land use and management (prior to the year 2000) are the basis for representative cropland management systems, selected by the entity landowner, that are used to initialize ("spinup") the DAYCENT model for computing soil organic carbon stock changes. The attributes of the management systems are based primarily on three large datasets for the US: the National Resources Inventory (NRI), the National Agricultural Statistics Service (NASS) cropland surveys, and USDA Economic Research Service Cropping Practices Survey. The use of representative crop management systems for the DAYCENT initialization process introduces some uncertainty when applied to a specific farm or ranch entity (which has a unique management history that may be different from the regionally-based representative management histories specified by Major Land Resource Areas. However, the major uncertainty for the model initialization is driven by the timing of major land-cover change (e.g., conversion of grassland to cropland) which can be user-specified for the particular entity and land parcel.

National Resources Inventory. The NRI is an inventory of land cover and use, soil erosion, prime farmland, wetlands, and other natural resource characteristics. NRI was designed as a tool to assess conditions and trends for soil, water, and related natural resources primarily on non-Federal lands of the United States (Nusser and Goebel, 1997). The NRI is a stratified two-stage area sample of over several hundred thousand points distributed across the United States and Caribbean. Each point in the survey is assigned an area weight (i.e., expansion factor) based on other known areas and land-use information so that each point has a statistically assigned area that it represents (Nusser and Goebel, 1997). It should be noted that there is some uncertainty associated with scaling the point data to a region or the country using the expansion factors. In general, those uncertainties decline at larger scales, such as States compared to smaller county units, because of a larger sample size.

National Agricultural Statistics Service Crop Surveys. Data from the NASS county agricultural production surveys were used to construct representative crop rotations for the period prior to (i.e., before 1979) the data record in the NRI. NASS conducts thousands of surveys each year covering many facets of U.S. agriculture. Estimates include crop acreage, yield, production, irrigation, and livestock numbers. State-level crop estimates are available from as early as 1866 depending on the State and variable of interest. Some county-level crop data is available from as early as 1915, with most crops available for most States by about 1960. Data aggregated to the county level are subject to a high level of quality control, including data screening for outliers, double checking with primary data collectors and comparisons with other aggregate data sets such as from the USDA Farm Services Agency.

USDA Economic Research Service (ERS) Cropping Practices Survey. Ancillary data on historical management practices used in the DAYCENT model initialization include nitrogen fertilizer rates (USDA ERS, 1997; 2011). Mean fertilizer rates since 1990 were estimated for all major crops, summarized by ERS at the State-level. If a State was not surveyed for a particular crop or if there were not enough data to produce a State level estimate, then data were aggregated to USDA Farm Production Regions in order to estimate a mean and standard deviation for fertilization rates (Farm Production Regions are groups of States with similar agricultural commodities). Crop-specific regional fertilizer rates prior to 1990 were based largely on extrapolation or interpolation of fertilizer rates from the years with available data. For crops in some agricultural regions, little or no data were available, and, therefore, a geographic regional mean was used to simulate nitrogen fertilization rates (e.g., no data are available for the State of Alabama during the 1970s and 1980s for corn fertilization rates; therefore, mean values from the southeastern United States were used to simulate fertilization to corn fields). No uncertainty data are available for this dataset.

8.1.3.10 DNDC Input Datasets

The DeNitrification-DeComposition (DNDC) model is proposed to estimate GHG emissions and removals from wetlands systems. DNDC is a soil biochemistry model that simulates thermodynamic and reaction kinetic processes of carbon, nitrogen, and water driven by the plant and microbial activities in ecosystems (Olander and Haugen-Kozyra, 2011). The DNDC model relies on specific input datasets that can be categorized into five sources: (1) cropland/land-use data; (2) crop management data; (3) soils data; (4) weather data; and (5) atmospheric deposition data (Salas et al., 2012). These primary sources of data and uncertainty associated with the dataset are provided below.

National Agricultural Statistics Service Cropland Data Layer dataset. The DNDC model uses the NASS Cropland Data Layer as a source of cropland/land-use data. The NASS Cropland Data Layer is an online geospatial exploring tool generated from satellite image observations at a 30 meter resolution. NASS provides accuracy information and error matrices (total accuracy, errors of omission and co-mission), but not on an annual basis for crops and States.

NASS Agricultural Census. The census is available every five years, and used at the county scale. It provides information on U.S. farms and ranches and is the only source of uniform, comprehensive agricultural data at the county level. Farmers and ranchers are asked to respond to the census by mail or online. Information including production expenses, market value of products, and operation characteristics are a few of the categories of data. Uncertainty is not assessed for these data.

Remote Sensing. DNDC uses remote sensing to build regional databases on cropland on a project and as needed basis. The range of sensors used includes RapidEye, Landsat, MODIS, and SAR (PALSAR, Radarsat, ENVISAT, etc.). Remote sensing is used for estimating hydroperiods (i.e., where the water table is at any given time). As DNDC does not have a groundwater modeling component, remote sensing is used to identify when wetlands are flooded. Uncertainty is not assessed for these data.

USDA, ERS Agricultural Resource Management Survey (ARMS). ARMS data are used to populate the crop management component of the DNDC module. USDA ERS ARMS provide data on the financial condition, production practices, and resource use of farmers at the field level within the United States. ARMS data are released and/or revised twice a year. Uncertainty is not assessed for these data.

CONUS STATSGO (See description above). These data are used to associate soil types and uncertainty of soils data within the model.

SSURGO (See description above). SSURGO data are retrieved by DNDC via an automated retrieval script and extract four key soil attributes: clay content (texture), bulk density, organic matter (soil organic carbon), and pH.

NOAA National Climatic Data Center. DNDC uses station data from the NOAA National Climatic Data Center (NCDC) to input temperature, dew point, relative humidity, precipitation, wind speed and direction, visibility, and atmospheric pressure. Data are provided at the subhourly, hourly, daily, monthly, annual, and multiyear timescale. NCDC provides values that describe the range of the uncertainty, or simply "range," of each month, season, or year global temperature anomaly. These values can be used as plus/minus values within an overall Monte Carlo framework; however, a tool is needed to utilize this information.

Daymet (See description above). These weather data are used by DNDC and have been available for much of North America from 1980 to 2012. Uncertainty information is not available for this dataset.

National Aeronautics and Space Administration Modern-Era Retrospective Analysis for Research and Applications (MERRA). The DNDC model relies on MERRA satellite data as input for the hydrological cycle. MERRA provides global data on various aspects of moisture distribution and variability. Nearly 30 years of data are available and has undergone an online bias correction for satellite radiance observations. This was done to calibrate observations from different satellites. Uncertainty data are not available for MERRA output.

National Oceanic and Atmospheric Administration National Center for Environmental Prediction (NCEP). DNDC inputs NCEP national weather, water, and climate data into the NCEP model. NCEP creates climate, water, ocean, space, and environmental hazard outputs. Uncertainty data are not available for NCEP output.

National Atmospheric Deposition Program National Trends Network (NTN) Stations. DNDC requires total nitrogen deposition and estimates of average concentration. DNDC relies on the NADP NTN stations to input total nitrogen deposition (NO_3 and NH_4) into the model. NADP NTN stations collect precipitation and chemistry samples away from urban area and point sources of pollution. The station's Central Analytical Laboratory reviews data for completeness and accuracy and flags samples that were mishandled or compromised. Sample data are further reviewed by the NADP program office to do a final check to resolve discrepancies. Once data are made available online, DNDC calculates mean nitrogen deposition for the simulation time period and incorporates the data into the project database. NADP NTN station data do not have associated uncertainty data available, however regional uncertainty was analyzed in a presentation by Dennis et al. (2011).

8.1.3.11 Approach for Incorporating Large Dataset Uncertainty

Among the large datasets to be used for the GHG quantification methods, only GTR-NE-343 has some quantified uncertainty information for use in a Monte Carlo assessment of net GHG emissions. Because confidence intervals for only two stock volumes are available, only a linear relationship can be modeled with GTR-NE-343 information, and no departures from linearity can be assessed. Further analysis of carbon density at other growing stock volumes requires computation of additional confidence intervals.

Given the lack of uncertainty information for most of the relevant large datasets, estimating this source of uncertainty is not feasible. Instead, reliance of the methods on the large datasets is explicitly acknowledged and readily available information on uncertainty is summarized as provided above.

Some large “wall-to-wall” datasets are formed via interpolation of existing data from a fixed set of measurement locations. For such datasets, a potential near-term next step might be to incorporate uncertainty by imputing measurements from randomly-selected measurement locations. This random selection could use probabilities inversely proportional to the distance between the measurement locations and the entity. If most locations are far from the entity, then the imputations are increasingly uncertain.

In the longer term, both new research and synthesis of existing research will be required to quantify large dataset uncertainty. Methods from geostatistics, for example, might be used to describe an uncertain large dataset obtained by interpolation.

8.1.4 Model Uncertainty

In the case of the external models, it is hard to appropriately account for approximation error and often only one model exists to represent or estimate emissions (or removals) from a specific activity or process. Since comparable models do not exist, it is almost impossible to estimate the uncertainty associated with using one particular model versus another. While this report specifies the use of several external models—DAYCENT, DNDC, FVS, i-Tree Canopy, i-Tree Eco, First Order Fire Effects Model (FOFEM)—given the above considerations, limited published data was found on external model uncertainty inherent with these models.

This section includes a description of the external models used for estimating carbon stocks and stock changes from the croplands and grazing lands, wetlands, and forestry sectors, uncertainty information obtained from the model developers. These models help provide a quantitative and geographical view into the emissions associated with a variety of factors from agricultural and forestry systems. For example, given inputs such as area, tree diameter, tree height, species, soil type, and geography, the suite of forestry models can provide emission estimates from fire disturbances, approximate changes in forest carbon stocks, or provide urban forest carbon stock data. Table 8-2 below summarizes the uncertainty information obtained from the model developers for each of the models used to estimate net GHG emissions. Given the lack of quantitative information on model uncertainty, this component of uncertainty will not be part of the Monte Carlo uncertainty assessment.

Table 8-2: Uncertainty Information for Process-based Models

Model	Availability of Uncertainty Documentation	Occurrence of Uncertainty Biases
DAYCENT	Ogle et al., 2010	Biases by practice are quantified in Ogle et al. (2010).
DNDC[a]	Input uncertainty: Li et al. (2002) and Zhang et al. (2009). There have been	A Monte Carlo approach or Most Sensitive Factor analysis can be run on certain input parameters

Model	Availability of Uncertainty Documentation	Occurrence of Uncertainty Biases
	no papers focused on quantification of DNDC model structural uncertainty.	(i.e., soil measurements) to assess the variability of the parameters (includes excerpts from C_AGG whitepaper by Salas et al., 2012).
Forest Vegetation Simulator	No published quantification of model uncertainty was found.	Exists but not quantifiable according to experts.
i-Tree Canopy (Aerial Data Method)	No published quantification of model uncertainty found.	Model bias is likely low, according to model developer.
i-Tree Eco (Field Data Method)	No published quantification of model uncertainty found.	Values are standardized, bias is minimized. Unknown bias for national density estimates.
First Order Fire Effects Model	No published quantification of model uncertainty found.	Regional biases (North Rocky Mountains, Pacific Northwest regions).

[a] DNDC does not provide uncertainty parameterization of outputs at the site level, however, the regional model provides an option for assessing uncertainty due to input uncertainty.

8.1.4.1 DAYCENT Model

The DAYCENT model has inherent uncertainty associated with predicting soil organic carbon (SOC) stock changes (Ogle et al., 2010; U.S. EPA, 2013). The uncertainty is associated with imperfect simulation of the plant and soil processes associated with the algorithms and parameters. To address this uncertainty, the simulated model predictions of SOC stocks need to be compared to measurements. The comparison leverages the scalability of the process-based model to the wide range of conditions that exist in agricultural lands, while having an underlying measurement basis to support the reporting (Conant et al., 2011).

The differences between measurements and simulated SOC stocks and stock changes have been analyzed using an empirically based approach in which a statistical model was developed that quantifies the accuracy and precision in the simulated predictions (Ogle et al., 2007). The linear mixed-effect modeling approach was used for this analysis, and various environmental conditions (e.g., climate and soil characteristics) and management practices were evaluated to determine if the model is more accurate or precise for particular conditions or management systems. The approach relied on measurements of SOC stocks from a network of sites across the U.S. agricultural lands. A network is currently being expanded by the USDA NRCS that is expected to provide additional measurements supporting the entity-scale methods for estimating SOC stock changes. This uncertainty analysis will be updated as new measurements become available from the network and will be incorporated into a Monte Carlo assessment.

8.1.4.2 DNDC Model

Structural uncertainty is related to the inherent uncertainty of a model that remains even if none of the input data had any variability. Estimating model structural uncertainty requires the use of independent validation data (i.e., field measurement data that were not used to develop the model algorithms). This approach requires not only access to sufficient independent field data, but also that the data include all the input data that DNDC requires. A number of validation tests with independent field data have been published although summary studies are currently not available to quantify DNDC structural uncertainty.

8.1.4.3 Forest Vegetation Simulator

As previously described, a source of uncertainty for the FVS model is sampling uncertainty associated with the tree list (the main user input). The additional uncertainty associated with the model uncertainty is difficult to quantify.

In the FVS model, diameter growth is the only variable that is considered stochastic. For the diameter growth module, a random seed is used for projections of changes in forest stands rather than using the mean diameter value to avoid underestimating growth. This process increases error propagation because the results of the diameter growth module are used to make further estimates in the model, e.g., using growth and yield equations (i.e., Jenkins equations). However, the stochasticity of diameter growth is not the main driver of model uncertainty. Uncertainty associated with the FVS model is complex because it is derived from 20 different regionally specific model variants that were developed independently. Each model run or analysis has to be calibrated to account for local tree variety and growth rates, introducing another level of complexity (Van Dyck, 2012). Additionally, errors may propagate from the bias in regional factors, adjusting to local geographies, climates, the use of field data, and sampling uncertainty. Given the overall complexity inherent in the model, FVS does not incorporate uncertainty in the output or post-analysis of model runs and additional research is required to quantify model uncertainty.

8.1.4.4 i-Tree Model

i-Tree (formerly the Urban Forest Effects model) is an urban forestry analysis model developed by David J. Nowak (USDA FS), Daniel E. Crane (NRS), and Patrick McHale (SUNY College of Environmental Science and Forestry). The i-Tree model helps quantify the structure of community trees and the environmental services that they provide. It provides six analytical tools including:

- **i-Tree Eco:** Provides a full picture of the entire urban forest (used in the Field Data Method)
- **i-Tree Streets:** Quantifies benefits from a municipalities street level trees
- **i-Tree Hydro:** Models the effects of trees on watershed stream flow and water quality
- **i-Tree Vue:** Uses NLCD satellite imagery to assess tree canopy
- **i-Tree Design:** Assesses multiple trees at parcel level
- **i-Tree Canopy:** Provides a quantifiable estimate of tree cover and other land cover types (using in the Aerial Data Method)

i-Tree Eco and i-Tree Canopy are recommended in this report for use by an entity to estimate the change in carbon stocks in their urban forests.

i-Tree Eco Uncertainty Information: The i-Tree Eco model produces uncertainty estimates based on sampling error, but it does not calculate a model estimation error. According to i-Tree developers, estimation error is based on the uncertainty inherent in the biomass conversion equations and emission factors. The developers also note that model bias is likely low given that the input assumes a given random sample of trees, and tree species equations are selected based on stand height. If a particular species equation is not available the model uses the average of available equations from the closest genera (Nowak, 2012). A Monte Carlo analysis tool could use the standard error of the estimated carbon value to evaluate the uncertainty associated with an entity's total net GHG emissions.

i-Tree Canopy Uncertainty Information: The i-Tree Canopy model produces a statistical estimate of the standard error of the percent tree cover estimate based on the ratio of sample points classified as trees to total sample points. In i-Tree Canopy the user imports a shape file, samples points, and classifies them as either trees or non-trees. An analysis of the tree point to total point ratio is used to estimate the standard error associated with the percent tree cover estimate, as described in the i-Tree Canopy technical notes,[18] and shown in Equation 8-1 below.

Equation 8-1: Estimating Standard Error of Percent Tree Cover from i-Tree Canopy

$$SE = \sqrt{pq/N} \text{ (e.g., } \sqrt{0.33 \times 0.67/1000} = 0.0149)$$

Where:

N= Total number of sampled points (e.g., 1,000)

n = Total number of points classified as a tree (e.g., 330)

p = n/N (e.g., 330/1,000 = 0.33)

q = 1 – p (e.g., 1 – 0.33 = 0.67)

Table 8-3 shows estimates of the standard error as related to the ratio of tree points to total sample points (p value), where the total number of sampled points (N) equals 1,000.

Based on the standard error formula, standard error is greatest when p equals 0.5, and is least when p is very small or very large (see Table 8-3). A Monte Carlo analysis tool could use the standard error of the estimated percent tree cover value to evaluate the uncertainty associated with an entity's total net GHG emissions.

Table 8-3: Estimates of Standard Error (SE) (N = 1,000) of Percent Tree Cover from i-Tree Canopy with Varying p Values

p	SE
0.01	0.0031
0.1	0.0095
0.3	0.0145
0.5	0.0158
0.7	0.0145
0.9	0.0095
0.99	0.0031

8.1.4.5 *First Order Fire Effects Model*

FOFEM is a computational model for predicting tree mortality, fuel consumption, smoke production, and soil heating caused by either prescribed fire or wildfire. FOFEM was developed by the Intermountain Fire Sciences Laboratory in Missoula, MT, of the USDA Forest Service. First order fire effects are those characterized with the direct immediate consequences of a fire including GHG emission estimates. FOFEM is divided into four national regions: Pacific West, Interior West, North East, and South East. The model includes several forest cover types to provide an additional level of detail resolution. The quantitative output can be used in assessments after fire damage, in analyzing prescribed fire impacts, and modeling vulnerabilities in regional forest groups.

FOFEM has a regional bias given that the empirical relationships and assumptions are based on forested systems in the North Rocky Mountains and the Pacific Northwest. However, these uncertainties are not quantified or adjusted for use in different regions. For instance, Southeast fires burn well at humidity levels that would not support them in the West. This phenomenon is not accounted for in the model and there is no uncertainty quantification around the output. There are also material differences such as litter bulk density that influences consumption and emission which can vary considerably region to region (Lutes, 2012).

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[18] I-Tree Canopy Technical Notes: http://www.itreetools.org/canopy/resources/iTree_Canopy_Methodology.pdf

8.1.4.6 Approach for Incorporating Model Uncertainty

Given the lack of uncertainty information for most of the relevant external models, it is not currently feasible for the GHG quantification methods to quantify this source of uncertainty. Instead, reliance of the methods on the models will be explicitly acknowledged. The potential impacts of uncertain models on the accuracy and precision of the resulting estimates is described qualitatively in the previous sections.

It may be possible in the near term to elicit expert judgments on the level of model uncertainty at the entity level. Models used in the GHG quantification methods are typically constructed at scales no smaller than the entity level. It is expected that the model uncertainty at the entity level would be no smaller than the model uncertainty at the model's scale, and possibly larger due to additional error from downscaling to the entity level.

In the longer term, more research is needed to evaluate model predictions with independent data, not used in the development of the model. The differences between model predictions and independent data are the best possible source of information regarding model uncertainty.

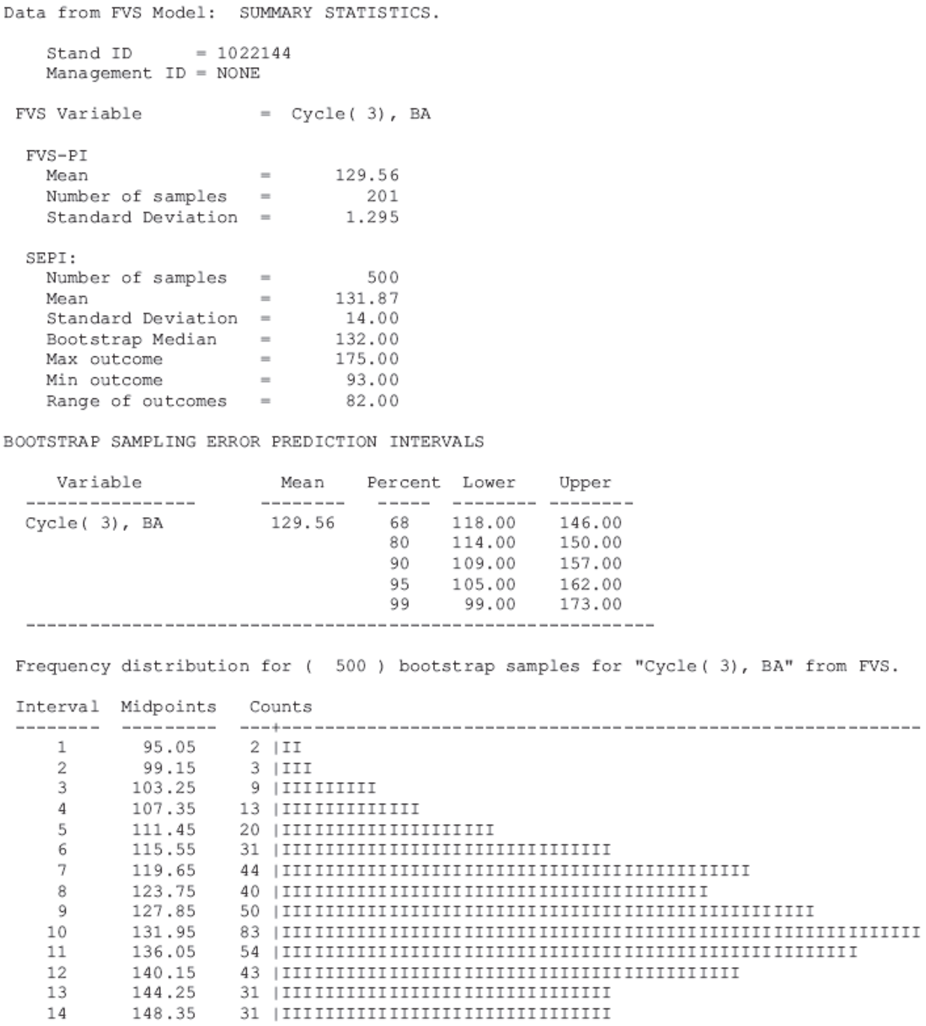
8.2 Research Gaps

The readily available information on parameter uncertainty is provided in the tables in Appendix 8-B. As indicated, much of the information to characterize the uncertainty is not available and the data that are provided are mostly default values from the literature and assumed probability density functions. To conduct a Monte Carlo analysis for uncertainty estimation, it is important to obtain probability density functions or summary statistics for all uncertain variables. Significant research is needed to obtain new data and to synthesize existing and new data in order to truly assess uncertainty associated with a range of factors causing uncertainty in the GHG estimates developed using the recommended methods described in this report. In particular, more research is needed to assess parameter, sampling, large data sets, and model uncertainties.

Appendix 8-A: Example Output File from FVS Sampling Uncertainty Bootstrapping Application FVSBoot (as provided in Gregg and Hummel, 2002)

The following table illustrates standard deviation surrounding the sampling error of the Basal Area outputs. FVSBoot can be configured to determine standard deviation of the sampling error for any FVS output.

Table 8-A-1: Example Output File from FVS Sampling Uncertainty Bootstrapping Application FVSBoot (as provided in Gregg and Hummel, 2002)



```
Data from FVS Model:  SUMMARY STATISTICS.

    Stand ID      = 1022144
    Management ID = NONE

 FVS Variable           =  Cycle( 3), BA

  FVS-PI
    Mean               =      129.56
    Number of samples  =         201
    Standard Deviation =       1.295

  SEPI:
    Number of samples  =         500
    Mean               =      131.87
    Standard Deviation =       14.00
    Bootstrap Median   =      132.00
    Max outcome        =      175.00
    Min outcome        =       93.00
    Range of outcomes  =       82.00

BOOTSTRAP SAMPLING ERROR PREDICTION INTERVALS

     Variable             Mean    Percent  Lower    Upper
  -----------------     --------   -----  -------- --------
  Cycle( 3), BA          129.56     68    118.00    146.00
                                    80    114.00    150.00
                                    90    109.00    157.00
                                    95    105.00    162.00
                                    99     99.00    173.00
  -----------------------------------------------------------

 Frequency distribution for (  500 ) bootstrap samples for "Cycle( 3), BA" from FVS.

 Interval  Midpoints   Counts
 --------  ---------   ---+-------------------------------------------------------------
     1        95.05    2 |II
     2        99.15    3 |III
     3       103.25    9 |IIIIIIIII
     4       107.35   13 |IIIIIIIIIIIII
     5       111.45   20 |IIIIIIIIIIIIIIIIIIII
     6       115.55   31 |IIIIIIIIIIIIIIIIIIIIIIIIIIIIIII
     7       119.65   44 |IIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIII
     8       123.75   40 |IIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIII
     9       127.85   50 |IIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIII
    10       131.95   83 |IIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIII
    11       136.05   54 |IIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIII
    12       140.15   43 |IIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIII
    13       144.25   31 |IIIIIIIIIIIIIIIIIIIIIIIIIIIIIII
    14       148.35   31 |IIIIIIIIIIIIIIIIIIIIIIIIIIIIIII
```

Appendix 8-B: Uncertainty Tables

This section presents readily available data on the uncertainty associated with activity and emission factor data. Table 8-B-1 lists the data elements that are provided in the subsequent tables for each agriculture system. In particular, readily available uncertainty information is provided in the following tables:

- Table 8-B-2: Cropland Uncertainty Template
- Table 8-B-3: Animal Population Uncertainty Template
- Table 8-B-4: Enteric Fermentation and Housing Uncertainty Template
- Table 8-B-5: Manure Management Uncertainty Table
- Table 8-B-6: Forestry Uncertainty Table

Table 8-B-1: Data Elements Provided

Column Label	Description
Data Element Name	The name of the variable
Abbreviation / Symbol	The shorthand representation used in the report
Emission Type	Emissions estimates that depend on the data element (CH_4, N_2O, NH_3, CO_2)
Data Input Unit	Unit associated with the data element
Input Source	Entity entry, default entry, model output, or from a database
Statistic	Available statistic for the parameter
Type of Statistic	Mean, median, or mode
Probability Distribution Type	The probability distribution function of the data element (normal, lognormal, uniform, triangular, beta)
Relative Uncertainty	Range of values around the most likely value, expressed as a percent of the most likely value
Confidence Level	The probability that the confidence range captures the true value of the data element given a distribution of samples.
Effective Lower Limit	Minimum value for data element (excluding outliers)
Effective Upper Limit	Maximum value for data element (excluding outliers)
Data Source	Reference for information related to the data element and associated uncertainty

Table 8-B-2: Cropland Uncertainty Template

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Croplands – Multiple Sub-sources	Area	A	CH_4, N_2O, CO_2	Hectares	Entity Entry									
Croplands – Multiple Sub-sources	Crop Yield	Y	CH_4, N_2O, CO_2	Metric tons dry matter crop yield/ year	Entity Entry									
Croplands – Multiple Sub-sources	Meat yield per parcel of land	Meat	CO_2	kg carcass yield	Entity Entry									
Croplands – Multiple Sub-sources	Milk production per parcel of land	Milk Prod.	CO_2	kg fluid milk yield	Entity Entry									
Biomass Carbon Stock Changes	Mean annual woody biomass (t=current year's stocks)	W_t	CO_2	Metric tons CO_2-eq $year^{-1}$	Model Output	DAYCENT model simulations and growth functions for agro-forestry								
Biomass Carbon Stock Changes	Mean annual woody biomass (t-1=Previous year's stocks)	W_{t-1}	CO_2	Metric tons CO_2-eq $year^{-1}$	Model Output	DAYCENT model simulations and growth functions for agro-forestry								
Biomass Carbon Stock Changes	Mean annual herbaceous biomass (t=current year's stocks)	H_t	CO_2	Metric tons CO_2-eq $year^{-1}$	Entity Entry									
Biomass Carbon Stock Changes	Mean annual herbaceous biomass (t-1=Previous year's stocks)	H_{t-1}	CO_2	Metric tons CO_2-eq $year^{-1}$	Entity Entry									

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Biomass Carbon Stock Changes	Forage Yield	Forage yield for grazing lands	CO_2	Metric tons dry matter per hectare	Entity Entry									
Biomass Carbon Stock Changes	Number of trees by age of diameter class for each agroforestry practice	Number of Trees	CO_2	Number	Entity Entry									
Biomass Carbon Stock Changes	Diameter at breast height for a subsample of trees	DBH	CO_2	Meters	Entity Entry									
Biomass Carbon Stock Changes	Root to Shoot Ratio	R:S	CO_2	Ratio	Default Entry									West et al. (2010)
Biomass Carbon Stock Changes	Dry matter content of harvested crop biomass or forage	DM	CO_2	Dimensionless	Entity Entry									
Biomass Carbon Stock Changes	Harvest Index	HI	CO_2	Fraction	Default Entry									West et al. (2010)
Biomass Carbon Stock Changes	Crop harvest or forage yield, corrected for moisture content	Y_{dm}	CO_2	Metric tons biomass ha^{-1}	Entity Entry									
Biomass Carbon Stock Changes	Approximate fraction of calendar year representing the growing season	Y_f	CO_2	Fraction	Entity Entry									
Biomass Carbon Stock Changes	Carbon fraction of aboveground biomass	C	CO_2	Fraction	Default Entry	0.45		Normal	11.0	11.0				IPCC (1997)
CO_2 from Liming	Annual application of lime	M	CO_2	Metric tons/ year	Entity Entry									

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
CO_2 from Liming	Metric tons CO_2 emissions per metric tons of lime	EF	CO_2	Metric tons C/metric tons lime	Default Entry	-0.04			46.0	46.0				West and McBride (2005)
CO_2 from Urea Fertilizer Application	Annual amount of urea fertilization	M	CO_2	Metric tons urea/year	Entity Entry									
CO_2 from Urea Fertilizer Application	Proportion of C in urea	EF	CO_2	Metric tons C/metric tons urea	Default Entry	0.2								de Klein et al. (2006)
Direct N_2O Emissions	Area of organic soils (histosols) drained on a parcel of land (ha)	A_{os}	N_2O	ha	Entity Entry									
Direct N_2O Emissions	Prior-year crop type		N_2O	Metric tons N $year^{-1}$ ha^{-1}	Entity Entry									
Direct N_2O Emissions	Emission rate modeled at 0 level of N input (N_t =0)	ER_0	N_2O	Metric tons N_2O-N $ha^{-1}year^{-1}$	Model Output									
Direct N_2O Emissions	Emission factor for the typical fertilization rate	$EF_{typical}$	N_2O	Metric tons N_2O-N metric $tons^{-1}$ N	Model Output									
Direct N_2O Emissions	Typical N fertilizer rate	N_{tf}	N_2O	Metric tons N ha^{-1} $year^{-1}$	Database									
Direct N_2O Emissions	Emission rate for the typical case modeled	$ER_{typical}$	N_2O	Metric tons N ha^{-1} $year^{-1}$	Model Output									
Direct N_2O Emissions	Actual N fertilizer rate, including synthetic and organic	N_f	N_2O	Metric tons N $year^{-1}$ ha^{-1}	Entity Entry									

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Direct N_2O Emissions	Base EF scalar for ΔN_f > zero and non-grassland crops	S_{EF}	N_2O	(metric tons N_2O-N (metric tons N)$^{-2}$) ha year	Default Entry	0.0274								Appendix 3-A
Direct N_2O Emissions	Base EF scalar for ΔN= > zero and grassland	S_{EF}	N_2O	(metric tons N_2O-N (metric tons N)$^{-2}$) ha year	Default Entry	0.117								Appendix 3-A
Direct N_2O Emissions	Base EF scalar for ΔN_f < zero	S_{EF}	N_2O	(metric tons N_2O-N (metric tons N)$^{-2}$) ha year	Default Entry	0								Appendix 3-A
Direct N_2O Emissions	Dry matter content of harvested biomass	DM	N_2O		Entity Entry									
Direct N_2O Emissions	Residue:yield ratios		N_2O	Ratio	Entity Entry									
Direct N_2O Emissions	Amount of residue harvested, burned or grazed	R_r	N_2O		Entity Entry									
Direct N_2O Emissions	Fraction of live biomass removed by grazing	F_r	N_2O		Entity Entry									
Direct N_2O Emissions	N mineralization from manure	N_{man}	N_2O		Entity Entry and Model Output									
Direct N_2O Emissions	N mineralization from compost	N_{comp}	N_2O		Entity Entry and Model Output									
Direct N_2O Emissions	Total dry matter yield of crop		N_2O	Metric tons dry matter year^{-1}	Entity Entry									
Direct N_2O Emissions	Stocking rates and methods		N_2O	Head/acre	Entity Entry									

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Direct N_2O Emissions	Scaling factor for slow-release fertilizers, 0 where no effect	S_{sr}	N_2O	Dimensionless	Default Entry	-0.21		Normal				-0.3	-0.12	Meta-analysis
Direct N_2O Emissions	Scaling factor nitrification inhibitors – semi-arid/arid climate	S_{inh}	N_2O	Dimensionless	Default Entry	-0.38		Normal				-0.51	-0.21	Meta-analysis
Direct N_2O Emissions	Scaling factor nitrification inhibitors – mesic climate	S_{inh}	N_2O	Dimensionless	Default Entry	-0.4		Normal				-0.52	-0.24	Meta-analysis
Direct N_2O Emissions	Scaling factor for no till, semi-arid/arid climate, <10 years following no-till adoption	S_{till}	N_2O	Dimensionless	Default Entry	0.38						0.04	0.72	van Kessel et al. (2012); Six et al. (2004)
Direct N_2O Emissions	Scaling factor for no till, semi-arid/arid climate, ≥10 years following no-till adoption	S_{till}	N_2O	Dimensionless	Default Entry	-0.33						-0.5	-0.16	van Kessel et al. (2012); Six et al. (2004)
Direct N_2O Emissions	Scaling factor for no till, mesic/wet climate, <10 years following no-till adoption	S_{till}	N_2O	Dimensionless	Default Entry	-0.015						-0.16	0.16	van Kessel et al. (2012); Six et al. (2004)
Direct N_2O Emissions	Scaling factor for no till, mesic/wet climate, ≥10 years following no-till adoption	S_{till}	N_2O	Dimensionless	Default Entry	-0.09						-0.19	0.01	van Kessel et al. (2012); Six et al. (2004)

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Direct N_2O Emissions	N in slow-release N fertilizer applied to the parcel of land	N_{sr}	N_2O	Metric tons N $year^{-1}$ ha^{-1}	Entity Entry									
Direct N_2O Emissions	N in manure amendments (and sewage sludge) added to the parcel	N_{man}	N_2O	Metric tons N $year^{-1}$ ha^{-1}	Entity Entry									
Direct N_2O Emissions	N excreted by cattle, poultry and swine directly on the parcel of land (metric tons N year-1 ha-1)	N_{prp}	N_2O	Metric tons N $year^{-1}$ ha^{-1}	Entity Entry									
Direct and Indirect N_2O Emissions	N in synthetic fertilizer applied to a parcel of land	Nsfert	N_2O	Metric tons N $year^{-1}$ ha^{-1}	Entity Entry									
Direct N_2O Emissions	N from a change in soil organic matter mineralization due to LUC or tillage change applied to a parcel of land	N_{min}	N_2O	Metric tons N $year^{-1}$	Entity Entry	DAYCENT model derived								
Direct N_2O Emissions	N fraction of aboveground biomass for the crop or forage	N_a	N_2O	Dimensionless	Entity Entry									
Direct N_2O Emissions	N fraction of belowground biomass for the crop or forage	N_b	N_2O	Dimensionless	Entity Entry									

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Indirect N_2O Emissions	Emission rate for cropped histosols,	ER_{OS}	N_2O	Metric tons N_2O-N ha^{-1} year^{-1}	Default Entry	0.008		Uniform				0.002	0.024	IPCC (2006)
Indirect N_2O Emissions	N fertilizer applied of organic origin including manure, sewage sludge, compost and other organic amendments	F_{ON}	N_2O	Metric tons N year^{-1}	Entity Entry									
Indirect N_2O Emissions	Fraction of NSN that volatizes as NH3 and NOx	FR_{SN}	N_2O	kg N kg^{-1} Nsfert	Default Entry	0.1		Uniform				0.03	0.3	IPCC (2006)
Indirect N_2O Emissions	Fraction or proportion of F_{ON} that volatizes as NH_3 and NO_x	FR_{ON}	N_2O	kg N kg^{-1} NON	Default Entry	0.2		Uniform				0.05	0.5	IPCC (2006)
Indirect N_2O Emissions	Emission factor for volatilized N or proportion of N volatilized as NH_3 and NO_x that is transformed to N_2O in receiving ecosystem	EF_{vol}	N_2O	kg N_2O-N kg^{-1} N	Default Entry	0.01		Uniform				0.002	0.05	IPCC (2006)
Indirect N_2O Emissions	Fraction or proportion of Nt that leaches or runs off	FR_{Leach}	N_2O	kg N kg^{-1} N	Default Entry	0.3		Uniform				0.1	0.8	IPCC (2006)

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Indirect N_2O Emissions	Emission factor for leached and runoff N or proportion of leached and runoff N that is transformed to N_2O in receiving ecosystem	EF_{Leach}	N_2O	kg N_2O-N kg^{-1} N	Default Entry	0.0075		Uniform				0.0005	0.02 5	IPCC (2006)
Methane from Wetland Rice Cultivation	Cultivation period for rice under i, j, and k conditions	t_{ijk}	CH_4	Days	Entity Entry									
Methane from Wetland Rice Cultivation	Annual harvested area of rice for i, j, and k conditions	A_{ijk}	CH_4	Hectares/ year	Entity Entry									
Methane from Wetland Rice Cultivation	Application rate of organic amendment(s)	ROA_i	CH_4	Metric tons/ hectare	Entity Entry									
Methane from Wetland Rice Cultivation	Baseline emission factor for continuously flooded fields without organic amendments	EF_c	CH_4	kg CH_4/ha/ day	Default Entry	1.3		Uniform				0.8	2.2	IPCC (2006)
Methane from Wetland Rice Cultivation	Water regime during the cultivation period – Scaling Factor	SF_w for continuously flooded	CH_4	Scaling Factor from IPCC	Default Entry	1		Uniform				0.79	1.26	IPCC (2006)
Methane from Wetland Rice Cultivation	Water regime during the cultivation period – Scaling Factor	SF_w for single aeration	CH_4	Scaling Factor from IPCC	Default Entry	0.6		Uniform				0.46	0.8	IPCC (2006)

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Methane from Wetland Rice Cultivation	Water regime during the cultivation period – Scaling Factor	SF_w for multiple aerations	CH_4	Scaling Factor from IPCC	Default Entry	0.52		Uniform				0.41	0.66	IPCC (2006)
Methane from Wetland Rice Cultivation	Water regime before the cultivation period – Scaling factor	SF_p for non-flooded pre-season <180 days	CH_4	Scaling Factor from IPCC	Default Entry	1		Uniform				0.88	1.14	IPCC (2006)
Methane from Wetland Rice Cultivation	Water regime before the cultivation period – Scaling factor	SF_p for non-flooded pre-season > 180 days	CH_4	Scaling Factor from IPCC	Default Entry	0.68		Uniform				0.58	0.8	IPCC (2006)
Methane from Wetland Rice Cultivation	Water regime before the cultivation period – Scaling factor	SF_p for flooded pre-season > 30 days	CH_4	Scaling Factor from IPCC	Default Entry	1.9		Uniform				1.65	2.18	IPCC (2006)
Methane from Wetland Rice Cultivation	Organic amendment used – scaling factor	SF_o	CH_4	Scaling Factor from IPCC	Default Entry									
Methane from Wetland Rice Cultivation	Organic amendment conversion factor	$CFOA_i$ for straw incorporation less than 30 days before cultivation	CH_4	Conversion factor from IPCC	Default Entry	1		Uniform				0.97	1.04	IPCC (2006)
Methane from Wetland Rice Cultivation	Organic amendment conversion factor	$CFOA_i$ for straw incorporation more than 30 days before cultivation	CH_4	Conversion factor from IPCC	Default Entry	0.29		Uniform				0.2	0.4	IPCC (2006)

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Methane from Wetland Rice Cultivation	Organic amendment conversion factor	$CFOA_i$ for compost	CH_4	Conversion factor from IPCC	Default Entry	0.05		Uniform				0.01	0.08	IPCC (2006)
Methane from Wetland Rice Cultivation	Organic amendment conversion factor	$CFOA_i$ for farm yard manure	CH_4	Conversion factor from IPCC	Default Entry	0.14		Uniform				0.07	0.2	IPCC (2006)
Methane from Wetland Rice Cultivation	Organic amendment conversion factor	$CFOA_i$ for green manure	CH_4	Conversion factor from IPCC	Default Entry	0.5		Uniform				0.3	0.6	IPCC (2006)
Methane Uptake by Soils	Potential CH_4 Oxidation in soils	PCH_4 for grassland	CH_4	kg CH_4 ha^{-1} $year^{-1}$	Default Entry	3.2		Normal				0	6.9	Del Grosso et al. (2000)
Methane Uptake by Soils	Potential CH_4 Oxidation in soils	PCH_4 for coniferous forest	CH_4	kg CH_4 ha^{-1} $year^{-1}$	Default Entry	2.8		Normal				0.1	5.5	Del Grosso et al. (2000)
Methane Uptake by Soils	Potential CH_4 Oxidation in soils	PCH_4 for deciduous forest	CH_4	kg CH_4 ha^{-1} $year^{-1}$	Default Entry	11.8		Normal				1.9	21.6	Del Grosso et al. (2000)
Methane Uptake by Soils	CH_4 oxidation attenuation factor: cropland including set-aside (CRP) grassland, grazing land, and fertilized or recently harvested forests	AF	CH_4	N/A	Default Entry	0.30		Normal				0.07	1	Smith et al. (2000)
Methane Uptake by Soils	CH_4 oxidation attenuation factor: natural vegetation, 0-100 years after abandonment of agricultural production or timber harvest	AF	CH_4	N/A	Default Entry	0.3 + (0.007 × years since abandonment)		Normal				0.07 + (0.007 × years since abandonment)	1	Smith et al. (2000)

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Methane Uptake by Soils	CH_4 oxidation attenuation factor:>100 years post-management or never used for agricultural management or timber harvest	AF	CH_4	N/A	Default Entry	1		Normal				0.07	1	Smith et al. (2000)
N_2O from Wetland Rice	Total N inputs from all agronomic sources: mineral fertilizer, organic amendments, residues, and additional mineralization from LUC or tillage change (metric tons N year^{-1})	N_t	N_2O	Metric tons N year^{-1}	Entity Entry									
N_2O from Wetland Rice	Fertilizer N management		N_2O	Rate	Entity Entry									
N_2O from Wetland Rice	Organic fertilizer N		N_2O	% N	Entity Entry									
N_2O from Wetland Rice	Crop residue N		N_2O	% N	Entity Entry									
N_2O from Wetland Rice	Emission factor or proportion of N_t transformed to N_2O	EF	N_2O	kg N_2O-N (kg N)$^{-1}$	Default Entry	0.0022		Normal	0.2%	0.2%				Akiyama et al. (2005)
N_2O from Wetland Rice	Scaling factor to account for drainage effects	SF_D for continuously flooded systems	N_2O	Dimensionless	Default Entry	0								Akiyama et al. (2005)

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
N_2O from Wetland Rice	Scaling factor to account for drainage effects	SF_D for aerated systems	N_2O	Dimensionless	Default Entry	0.59		Normal	0.4%	0.4%				Akiyama et al. (2005)
Non CO_2 Emissions Biomass Burn	Boreal Forest (all)	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.34		Normal	102%	102%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Wildfire	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.4		Normal	340%	340%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Crown fire	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.43		Normal	104%	104%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Surface fire	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.15		Normal	96%	96%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Post logging slash burn	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.33		Normal	130%	130%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Temperate Forest (all)	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.45		Normal	51%	51%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Post logging slash burn	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.62		Normal	264%	264%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Shrublands (all)	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.72		Normal	147%	147%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	*Calluna* health	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.71		Normal	121%	121%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Fynbos	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.61		Normal	195%	195%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Savanna woodlands (early dry season burns) (all)	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.4		Normal	93%	93%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Savanna woodlands (mid/late dry season burns) (all)	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.74		Normal	99%	99%				IPCC (2006)

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Non CO_2 Emissions Biomass Burn	Savanna woodland (mid/late)	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.72		Normal	270%	270%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Tropical savanna	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.73		Normal	598%	598%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Other savanna woodlands	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.68		Normal	931%	931%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Savanna grasslands (early dry season burns) (all)	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.74		Normal	183%	183%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Tropical/sub-tropical grassland	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.74		Normal	270%	270%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Tropical/sub-tropical grassland	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.92		Normal	151%	151%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Tropical pasture	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.35		Normal	427%	427%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Savanna	Combustion Efficiency (C)	CH_4/N_2O		Default Entry	0.86		Normal	85%	85%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Emission factor	EF for grassland	CH_4	g GHG/kg burned biomass	Default Entry	2.3	Mean	Normal	8.0%	8.0%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Emission factor	EF for crop residue	CH_4	g GHG/kg burned biomass	Default Entry	2.7	Mean	Normal	50.0%	50.0%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Emission factor	EF for grassland	N_2O	g GHG/kg burned biomass	Default Entry	0.21	Mean	Normal	93.0%	93.0%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Emission factor	EF for crop residue	N_2O	g GHG/kg burned biomass	Default Entry	0.07	Mean	Normal	50.0%	50.0%				IPCC (2006)

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Non CO_2 Emissions Biomass Burn	Combustion efficiency	C for shrublands	CH_4/N_2O	% Burned	Default Entry	0.72	Mean	Normal	68.0%	68.0%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Combustion efficiency	C for grasslands with early season burns	CH_4/N_2O	% Burned	Default Entry	0.74	Mean	Normal	50.0%	50.0%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Combustion efficiency	C for grasslands with mid to late season burns	CH_4/N_2O	% Burned	Default Entry	0.77	Mean	Normal	66.0%	66.0%				IPCC (2006)
Non CO_2 Emissions Biomass Burn	Combustion efficiency	C for small grains	CH_4/N_2O	% Burned	Default Entry	0.9	Mean	Normal	50.0%	50.0%				Expert Assessment
Non CO_2 Emissions Biomass Burn	Combustion efficiency	C for large grain and other crop residues	CH_4/N_2O	% Burned	Default Entry	0.8	Mean	Normal	50.0%	50.0%				Expert Assessment
Non CO_2 Emissions Biomass Burn	Moisture content of residues and forage		CH_4/N_2O	% moisture	Default Entry									
Non CO_2 Emissions Biomass Burn	Residue to yield ratio of crop	R:Y	CH_4/N_2O	Metric tons residue / metric tons dry matter yield	Default Entry									
SOC Change Mineral Soils	Soil organic C stock at the end of the year	SOC_t	CO_2	Metric tons C ha^{-1}	Model Output	DAYCENT Model derived								Ogle et al. (2007); EPA (2013)

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
SOC Change Mineral Soils	Soil organic C stock at the beginning of the year	SOC_{t-1}	CO_2	Metric tons C ha^{-1}	Model Output	DAYCENT Model derived								Ogle et al. (2007); EPA (2013)
SOC Change Mineral Soils	Crop selection and Rotation Sequence		CO_2	Management List Developed by Experts	Entity Entry									
SOC Change Mineral Soils	Irrigation application rate		CO_2	Gallons per minute	Entity Entry									
SOC Change Mineral Soils	Mineral Fertilizer application Rate		CO_2	lbs/square foot	Entity Entry									
SOC Change Mineral Soils	Lime Amendment application Rate		CO_2	lbs/square foot	Entity Entry									
SOC Change Mineral Soils	Organic Amendment application Rate		CO_2	lbs/square foot	Entity Entry									
SOC Change Mineral Soils	Number of passes in each operation		CO_2	Number	Entity Entry									
SOC Change Mineral Soils	Depth of drainage		CO_2	Meters	Entity Entry									
SOC Change Mineral Soils	Length of field		CO_2	Meters	Entity Entry									
SOC Change Mineral Soils	Historical Weather Patterns		CO_2	PRISM Weather Data	Model Output									
SOC Change Mineral Soils	Physical and Chemical Properties of Soil		CO_2	NRCS SURRGO database	Model Output									
SOC Change Mineral Soils – Grazing Land	Animal Size used for grazing		CO_2	lbs	Entity Entry									

Cropland Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
SOC Change Mineral Soils – Grazing Land	Stocking Rate		CO_2	Head/acre	Entity Entry									
SOC Change Mineral Soils – Grazing Land	Irrigation application rate		CO_2	Gallons per minute	Entity Entry									
SOC Change Mineral Soils – Grazing Land	Mineral Fertilizer application Rate		CO_2	lbs/square foot	Entity Entry									
SOC Change Mineral Soils – Grazing Land	Depth of drainage		CO_2	Meters	Entity Entry									
SOC Change Organic Soils	Emission factor	EF for cropland in cool temperate regions	CO_2	Metric tons C $ha^{-1} year^{-1}$	Default Entry	11	Mean	Normal	45.0	45.0				Ogle et al. (2003)
SOC Change Organic Soils	Emission factor	EF for cropland in warm temperate regions	CO_2	Metric tons C $ha^{-1} year^{-1}$	Default Entry	14	Mean	Normal	35.0	35.0				Ogle et al. (2003)
SOC Change Organic Soils	Emission factor	EF for cropland in subtropical regions	CO_2	Metric tons C $ha^{-1} year^{-1}$	Default Entry	14	Mean	Normal	46.0	46.0				Ogle et al. (2003)
SOC Change Organic Soils	Emission factor	EF for grazing land in cool temperate regions	CO_2	Metric tons C $ha^{-1} year^{-1}$	Default Entry	2.8	Mean	Normal	45.0	45.0				Ogle et al. (2003)
SOC Change Organic Soils	Emission factor	EF for grazing land in warm temperate regions	CO_2	Metric tons C $ha^{-1} year^{-1}$	Default Entry	3.5	Mean	Normal	35.0	35.0				Ogle et al. (2003)
SOC Change Organic Soils	Emission factor	EF for grazing land in subtropical regions	CO_2	Metric tons C ha-1 year-1	Default Entry	3.5	Mean	Normal	46.0	46.0				Ogle et al. (2003)

Table 8-B-3: Animal Population Uncertainty Template

Animal Population Data Element Name	Abbreviation/ Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative Uncertainty Low (%)	Relative Uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Number of Animals													
Beef replacement heifers	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Dairy replacement heifers	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Mature beef cows	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Steers (>500 lbs)	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Bulls	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Stockers (All)	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Cattle on feed	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Dairy cow	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Cattle	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
American bison	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Sheep NOF	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Feedlot sheep	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Goats	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Horses	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment
Mules/burros/asses	N	CH_4, N_2O		Entity Entry				-1.0%	1.0%				Expert Assessment

Table 8-B-4: Enteric Fermentation and Housing Uncertainty Template

Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Daily Milk Production	Milk	CH_4	kg milk/animal/day	Entity Entry				3%	5%				Expert Assessment
Days in milk	DIM	CH_4	Days	Entity Entry									
Dry matter intake	DMI	CH_4	kg/animal/day	Entity Entry									
Daily Work Done by Animal	Work	CH_4	Hours/day	Entity Entry									
Average live body weight – lactating beef cows	BW	CH_4	kg	Entity Entry									
Beef Cow Mature Weight	MW	CH_4	lbs	Entity Entry									
Steer Daily Weight Gain to 24 months	WG	CH_4	lbs/day	Entity Entry									
Beef Steer Mature Weight	MW	CH_4	lbs	Entity Entry									
Beef Heifer Mature Weight	MW	CH_4	lbs	Entity Entry									
Net energy required by the animal for maintenance	NE_m	CH_4	MJ day^{-1}	Entity Entry									
Milk Fat Content	Fat	CH_4	Percent	Entity Entry									
Starch Content of Diet (Dairy Cows)	Starch	CH_5	kg/animal/day	Entity Entry									
Acid Detergent Fiber Content of Diet	ADF	CH_4	kg/head/day	Entity Entry									
DE – Each Feed Type	DE	CH_4	Percent of gross energy	Entity Entry									
Neutral Detergent Fiber in Diet (Dairy Cows)	NDF	CH_4	Percent	Entity Entry									
Crude Protein in Diet	CP	CH_4	Percent	Entity Entry									
Acid Detergent Fiber Content of Diet (Dairy Cows)	ADF	CH_4	Percent	Entity Entry									
Neutral Detergent Fiber in Diet	NDF	CH_4	Percent	Entity Entry									
Supplemental Fat (feedlot)	S.Fat	CH_4	Percent	Entity Entry	3%	Mean					2	4	Expert Assessment
Dietary Forage %		CH_4	Percent	Entity Entry									
Total Digestible Nutrients (Dairy Cows)	TDN	CH_4	kg	Entity Entry									
Ym Feedlot – All Regions	Ym	CH_4	% GE converted to CH_4	Default Entry									
Ym Beef Cattle Not on Feed (stocker)	Ym	CH_4	% GE converted to CH_4	Default Entry									
Ym Beef Cattle Not on Feed (all foraging animals except dairy)	Ym	CH_4	% GE converted to CH_4	Default Entry									

Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Ym Dairy Repl. Heif. – California	Ym	CH_4	% GE converted to CH_4	Default Entry									
Ym Dairy Repl. Heif. – West	Ym	CH_4	% GE converted to CH_4	Default Entry									
Ym Dairy Repl. Heif. – Northern Great Plains	Ym	CH_4	% GE converted to CH_4	Default Entry									
Ym Dairy Repl. Heif.– Southcentral	Ym	CH_4	% GE converted to CH_4	Default Entry									
Ym Dairy Repl. Heif. – Northeast	Ym	CH_4	% GE converted to CH_4	Default Entry									
Ym Dairy Repl. Heif. – Midwest	Ym	CH_4	% GE converted to CH_4	Default Entry									
Ym Dairy Repl. Heif. – Southeast	Ym	CH_4	% GE converted to CH_4	Default Entry									
Maximum daily emissions for dairy cows	E_{max}	CH_4	MJ/head	Default Entry	45.98								Mills et al. (2003)
Average live body weight for lactating cows	BW	N_2O/NH_3	kg	Entity Entry									
Typical Ammonia Losses from Dairy Housing Facilities –Open dirt lots (cool, humid region)	NH_3 loss	$N_2O\ _3$	Percent of N_{ex}	Default Entry							15%	30%	Koelsh and Stowell (2005)
Typical Ammonia Losses from Dairy Housing Facilities –Open dirt lots (hot, arid region)	NH_3 loss	N_2O	Percent of N_{ex}	Default Entry							30%	45%	Koelsh and Stowell (2005)
Typical Ammonia Losses from Dairy Housing Facilities –Roofed facility (flushed or scraped) Roofed facility (daily scrape and haul)	NH_3 loss	N_2O	Percent of N_{ex}	Default Entry							5%	15%	Koelsh and Stowell (2005)
Typical Ammonia Losses from Dairy Housing Facilities –Roofed facility (shallow pit under floor)	NH_3 loss	N_2O	Percent of N_{ex}	Default Entry							10%	20%	Koelsh and Stowell (2005)
Typical Ammonia Losses from Dairy Housing Facilities –Roofed facility (bedded pack)	NH_3 loss	N_2O	Percent of N_{ex}	Default Entry							20%	40%	Koelsh and Stowell (2005)
Typical Ammonia Losses from Dairy Housing Facilities –Roofed facility (deep pit under floor, includes storage loss)	NH_3 loss	N_2O	Percent of N_{ex}	Default Entry							30%	40%	Koelsh and Stowell (2005)
Typical Ammonia Losses from Beef Housing Facilities – Open dirt lots (cool, humid region)	NH_3 loss	N_2O	Percent of N_{ex}	Default Entry							30%	45%	Koelsh and Stowell (2005)

Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Typical Ammonia Losses from Beef Housing Facilities – Open dirt lots (hot, arid region)	NH_3 loss	N_2O	Percent of N_{ex}	Default Entry							40%	60%	Koelsh and Stowell (2005)
Typical Ammonia Losses from Beef Housing Facilities –Roofed facility (bedded pack)	NH_3 loss	N_2O	Percent of N_{ex}	Default Entry							20%	40%	Koelsh and Stowell (2005)
Typical Ammonia Losses from Beef Housing Facilities –Roofed facility (deep pit under floor, includes storage loss)	NH_3 loss	N_2O	Percent of N_{ex}	Default Entry							30%	40%	Koelsh and Stowell (2005)
N_2O Emission Factor for manure in housing (dry lots and pit storage)	EF_{N2O}	N_2O	kg N_2O-N/kg N	Default Entry									IPCC (2006)
Nitrogen Excretion from Beef Cattle—Days on feed for an individual ration	DOF_x	N_2O, NH_3	Days	Entity Entry									
Nitrogen Excretion from Beef Cattle—Live body weight at finish of feeding period	BW_F	N_2O, NH_3	kg	Entity Entry									
Nitrogen Excretion from Beef Cattle—Live body weight at the start of feeding period	BW_I	N_2O, NH_3	kg	Entity Entry									
Nitrogen Excretion from Beef Cattle—Standard reference weight for expected final body fat	SRW	N_2O, NH_3	kg	Entity Entry									
Nitrogen Excretion from Beef Cattle—Concentration of crude protein of total ration	$C_{CP\text{-}x}$	N_2O, NH_3	g crude protein/g dry feed	Entity Entry									
Monthly Beef Feedlot NH_3 Emissions—Dietary crude protein	CP	NH_3	Percent of dry matter	Entity Entry									
Average monthly temperature	T	N_2O, NH_3	Degrees Kelvin	Entity Entry									
Nitrogen Excretion from Grow-Finish Pigs –Average daily feed intake over finishing period	$ADFI_G$	N_2O, NH_3	g/ day	Entity Entry									
Nitrogen Excretion from Grow-Finish Pigs –Concentration of crude protein of total (wet) ration	C_{CP}	N_2O, NH_3	Percent	Entity Entry									

Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Nitrogen Excretion from Grow-Finish Pigs –Days on feed to finish animal (grow-finish phase)	DOF_G	N_2O, NH_3	Days	Entity Entry									
Nitrogen Excretion from Grow-Finish Pigs –Final (market) body weight	BW_F	N_2O, NH_3	kg	Entity Entry									
Nitrogen Excretion from Grow-Finish Pigs –Average dressing percent (yield) at final weight	DP_F	N_2O, NH_3	Percent	Entity Entry									
Nitrogen Excretion from Grow-Finish Pigs –Initial body weight	BW_I	N_2O, NH_3	kg	Entity Entry									
Nitrogen Excretion from Grow-Finish Pigs –Average fat-free lean percentage at final weight	$FFLP_F$	N_2O, NH_3	Percent	Entity Entry									
Nitrogen Excretion from Weaning Pigs – Average daily feed intake over finishing period	$ADFI_G$	N_2O, NH_3	g/ day	Entity Entry									
Nitrogen Excretion from Weaning Pigs – Concentration of crude protein of total (wet) ration	C_{CP}	N_2O, NH_3	Percent	Entity Entry									
Nitrogen Excretion from Weaning Pigs – Days on feed to finish animal (nursery phase)	DOF_N	N_2O, NH_3	Days	Entity Entry									
Nitrogen Excretion from Weaning Pigs – Average fat-free lean gain from 20 to 120kg	FFLPG	N_2O, NH_3	g/ day	Entity Entry									
Nitrogen Excretion from Weaning Pigs – Final body weight in nursery phase	BW_{F-N}	N_2O, NH_3	kg	Entity Entry									
Nitrogen Excretion from Weaning Pigs – Initial body weight in nursery phase	BW_{I-N}	N_2O, NH_3	kg	Entity Entry									
Nitrogen Excretion from Gestating Sows –Average daily feed intake during gestation	$ADFI_S$	N_2O, NH_3	g/ day	Entity Entry									
Nitrogen Excretion from Gestating Sows –Concentration of crude protein	C_{CP}	N_2O, NH_3	Percent	Entity Entry									
Nitrogen Excretion from Gestating Sows –Gestation period length	GL	N_2O, NH_3	Days	Entity Entry									
Nitrogen Excretion from Gestating Sows –Gestation lean tissue gain	GLTG	N_2O, NH_3	Kg	Entity Entry									

Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Nitrogen Excretion from Gestating Sows –Number of pigs in litter	LITTER	N_2O, NH_3	Head	Entity Entry									
Nitrogen Excretion from Lactating Sows—Average daily feed intake during lactation	$ADFI_{LACT}$	N_2O, NH_3	g/ day	Entity Entry									
Nitrogen Excretion from Lactating Sows—Concentration of crude protein	C_{CP}	N_2O, NH_3	Percent	Entity Entry									
Nitrogen Excretion from Lactating Sows—Lactation length (days to weaning)	LL	N_2O, NH_3	Days	Entity Entry									
Nitrogen Excretion from Lactating Sows—Lactation lean tissue gain	LLTG	N_2O, NH_3	Kg	Entity Entry									
Nitrogen Excretion from Lactating Sows— Litter weight at weaning	L_{WEAN}	N_2O, NH_3	Kg	Entity Entry									
Nitrogen Excretion from Lactating Sows—Litter weight at birth	LW_{BIRTH}	N_2O, NH_3	kg	Entity Entry									
Typical Ammonia Losses from Swine Housing Facilities –Roofed facility (flushed or scraped) Roofed facility (daily scrape and haul)	$\%NH_3$ loss	NH_3	Percent of N_{ex}	Default Entry							5%	15%	Koelsh and Stowell (2005)
Typical Ammonia Losses from Swine Housing Facilities –Roofed facility (shallow pit under floor)	$\%NH_3$ loss	NH_3	Percent of N_{ex}	Default Entry							10%	20%	Koelsh and Stowell (2005)
Typical Ammonia Losses from Swine Housing Facilities –Roofed facility (bedded pack)	$\%NH_3$ loss	NH_3	Percent of N_{ex}	Default Entry							20%	40%	Koelsh and Stowell (2005)
Typical Ammonia Losses from Swine Housing Facilities –Roofed facility (deep pit under floor, includes storage loss)	$\%NH_3$ loss	NH_3	Percent of N_{ex}	Default Entry							30%	40%	Koelsh and Stowell (2005)
Nitrogen Excretion from Broilers, Turkeys, and Ducks—Feed intake per phase	FI_x	N_2O, NH_3	g feed/ finished animal	Entity Entry									
Nitrogen Excretion from Broilers, Turkeys, and Ducks—Concentration of crude protein of total ration in each phase	$C_{CP\text{-}X}$	N_2O, NH_3	g crude protein/ g (wet) feed	Entity Entry									

Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Nitrogen Excretion from Broilers, Turkeys, and Ducks—Retention factor for nitrogen	N_{RF}	N_2O, NH_3	Fraction	Entity Entry									
Nitrogen Excretion from Laying Hens—Feed intake	FI	N_2O, NH_3	g feed/ finished animal	Entity Entry									
Nitrogen Excretion from Laying Hens—Concentration of crude protein of total ration	C_{CP}	N_2O, NH_3	g crude protein/ g (wet) feed	Entity Entry									
Nitrogen Excretion from Laying Hens—Egg weight	Egg_{wt}	N_2O, NH_3	g	Entity Entry									
Nitrogen Excretion from Laying Hens—Fraction of eggs produced each day	Egg_{pro}	N_2O, NH_3	Eggs/ hen/ day	Entity Entry									
Typical Ammonia Losses from Poultry Housing –Roofed facility (litter) (Meat Producing birds)	%NH_3 loss	NH_3	Percent of N_{ex}	Default Entry							25%	50%	Koelsh and Stowell (2005)
Typical Ammonia Losses from Poultry Housing –Roofed facility (stacked manure under floor - , includes storage loss) (Egg-producing birds)	%NH_3 loss	NH_3	Percent of N_{ex}	Default Entry							25%	50%	Koelsh and Stowell (2005)
Methane Emissions from Goats – Emission factor for goats	EF_G	CH_4	kg CH_4/head/day	Default Entry	0.0137	Mean							IPCC (2006)
Methane Emissions from Bison – Emission factor for bison	EF_{AB}	CH_4	kg CH_4/head/day	Default Entry									

Table 8-B-5: Manure Management Uncertainty Template

Data Element Name	Data Element Abbreviation/Symbol	Emission Type	Data Input Unit	Input Type	Estimated Value	Type of Estimate	Relative uncertainty Low (%)	Relative uncertainty High (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Total Dry Manure – Beef Finishing Cattle		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	2.4	Mean	-20	20			ASABE (2005)
Total Dry Manure – Beef Cow (confinement)		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	6.6	Mean	-20	20			ASABE (2005)
Total Dry Manure – Beef Growing calf (confinement)		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	2.7	Mean	-20	20			ASABE (2005)
Total Dry Manure – Dairy Lactating cow		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	8.9	Mean	-20	20	8.7	11.3	ASABE (2005)
Total Dry Manure – Dairy Dry cow		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	4.9	Mean	-20	20	8.8	11.2	ASABE (2005)
Total Dry Manure – Dairy Heifer		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	3.7	Mean	-20	20			ASABE (2005)
Total Dry Manure – Dairy Veal 118 kg		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	0.12	Mean	-20	20			ASABE (2005)
Total Dry Manure – Horse Sedentary 500 kg		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	3.8	Mean	-20	20			ASABE (2005)
Total Dry Manure – Horse Intense exercise 500 kg		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	3.9	Mean	-20	20			ASABE (2005)
Total Dry Manure – Poultry Broiler		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	0.03	Mean	-20	20			ASABE (2005)
Total Dry Manure – Poultry Turkey (male)		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	0.07	Mean	-20	20			ASABE (2005)
Total Dry Manure – Poultry Turkey (females)		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	0.04	Mean	-20	20			ASABE (2005)
Total Dry Manure – Poultry Duck		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	0.04	Mean	-20	20			ASABE (2005)
Total Dry Manure – Layer		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	0.02	Mean	-20	20			ASABE (2005)
Total Dry Manure – Swine Nursery pig (12.5 kg)		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	0.13	Mean	-20	20			ASABE (2005)
Total Dry Manure – Swine Grow finish (70 kg)		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	0.47	Mean	-20	20			ASABE (2005)
Total Dry Manure – Swine gestating sow 200 kg		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	0.5	Mean	-20	20			ASABE (2005)

Data Element Name	Data Element Abbreviation/Symbol	Emission Type	Data Input Unit	Input Type	Estimated Value	Type of Estimate	Relative uncertainty Low (%)	Relative uncertainty High (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Total Dry Manure – Swine Lactating sow 192 kg		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	1.2	Mean	-20	20			ASABE (2005)
Total Dry Manure – Swine Boar 200 kg		CH_4, N_2O, NH_3	kg dry manure/animal/day	Entity Entry	0.38	Mean	-20	20			ASABE (2005)
Volatile solids – Beef Finishing cattle	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.81	Mean	-25	25			ASABE (2005)
Volatile solids – Beef Cow (confinement)	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.89	Mean	-25	25			ASABE (2005)
Volatile solids – Beef Growing calf (confinement)	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.85	Mean	-25	25			ASABE (2005)
Volatile solids – Dairy Lactating cow	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.84	Mean	-25	25			ASABE (2005)
Volatile solids – Dairy Dry cow	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.85	Mean	-25	25			ASABE (2005)
Volatile solids – Dairy Heifer	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.86	Mean	-25	25			ASABE (2005)
Volatile solids – Dairy Veal 118 kg	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry		Mean	-25	25			ASABE (2005)
Volatile solids – Horse Sedentary 500 kg	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.79	Mean	-25	25			ASABE (2005)
Volatile solids – Horse Intense exercise 500 kg	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.79	Mean	-25	25			ASABE (2005)
Volatile solids – Poultry Broiler	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.73	Mean	-25	25			ASABE (2005)
Volatile solids – Poultry Turkey (male)	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.8	Mean	-25	25			ASABE (2005)
Volatile solids – Poultry Turkey (females)	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.79	Mean	-25	25			ASABE (2005)
Volatile solids – Poultry Duck	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.58	Mean	-25	25			ASABE (2005)
Volatile solids – Layer	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.73	Mean	-25	25			ASABE (2005)
Volatile solids – Swine Nursery pig (12.5 kg)	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.83	Mean	-25	25			ASABE (2005)
Volatile solids – Swine Grow finish (70 kg)	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.8	Mean	-25	25			ASABE (2005)
Volatile solids – Swine gestating sow 200 kg	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.9	Mean	-25	25			ASABE (2005)
Volatile solids – Swine Lactating sow 192 kg	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.83	Mean	-25	25			ASABE (2005)
Volatile solids – Swine Boar 200 kg	VS	CH_4, N_2O	kg VS/kg dry manure	Entity Entry	0.89	Mean	-25	25			ASABE (2005)
Storage temperature	T	CH_4	Kelvin	Entity Entry							
Manure temperature	T_{manure}	NH_3	Kelvin	Entity Entry							
Ambient air velocity	V_a	NH_3	m/s	Default Entry							
Height	h	N_2O	m	Entity Entry							
Width	W	NH_3	m	Entity Entry							
Radius	r	NH_3	m	Entity Entry							
pH	pH	NH_3	-	Entity Entry	7.5				6.5	8.5	Expert Assessment

Data Element Name	Data Element Abbreviation/Symbol	Emission Type	Data Input Unit	Input Type	Estimated Value	Type of Estimate	Relative uncertainty Low (%)	Relative uncertainty High (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Total nitrogen at a given day – beef finishing cattle		N_2O	kg N/kg dry manure	Entity Entry	0.07	Mean					ASABE (2005)
Total nitrogen at a given day – beef cow (confinement)		N_2O	kg N/kg dry manure	Entity Entry	0.03	Mean					ASABE (2005)
Total nitrogen at a given day – beef growing calf (confinement)		N_2O	kg N/kg dry manure	Entity Entry	0.05	Mean					ASABE (2005)
Total nitrogen at a given day – dairy lactating cow		N_2O	kg N/kg dry manure	Entity Entry	0.05	Mean					ASABE (2005)
Total nitrogen at a given day – dairy dry cow		N_2O	kg N/kg dry manure	Entity Entry	0.05	Mean					ASABE (2005)
Total nitrogen at a given day – dairy heifer		N_2O	kg N/kg dry manure	Entity Entry	0.03	Mean					ASABE (2005)
Total nitrogen at a given day – dairy veal 118 kg		N_2O	kg N/kg dry manure	Entity Entry	0.13	Mean					ASABE (2005)
Total nitrogen at a given day – Horse Sedentary 500 kg		N_2O	kg N/kg dry manure	Entity Entry	0.02	Mean					ASABE (2005)
Total nitrogen at a given day – Horse Intense Exercise		N_2O	kg N/kg dry manure	Entity Entry	0.04	Mean					ASABE (2005)
Total nitrogen at a given day – poultry, broiler		N_2O	kg N/kg dry manure	Entity Entry	0.04	Mean					ASABE (2005)
Total nitrogen at a given day – poultry, turkey (male)		N_2O	kg N/kg dry manure	Entity Entry	0.06	Mean					ASABE (2005)
Total nitrogen at a given day – poultry, turkey (females)		N_2O	kg N/kg dry manure	Entity Entry	0.06	Mean					ASABE (2005)
Total nitrogen at a given day – poultry, duck		N_2O	kg N/kg dry manure	Entity Entry	0.04	Mean					ASABE (2005)
Total nitrogen at a given day – layer		N_2O	kg N/kg dry manure	Entity Entry	0.07	Mean					ASABE (2005)
Total nitrogen at a given day – swine nursery pig (12.5 kg)		N_2O	kg N/kg dry manure	Entity Entry	0.09	Mean					ASABE (2005)
Total nitrogen at a given day – swine grow finish (70 kg)		N_2O	kg N/kg dry manure	Entity Entry	0.08	Mean					ASABE (2005)
Total nitrogen at a given day – swine gestating sow 200 kg		N_2O	kg N/kg dry manure	Entity Entry	0.06	Mean					ASABE (2005)
Total nitrogen at a given day – swine lactating sow 192 kg		N_2O	kg N/kg dry manure	Entity Entry	0.07	Mean					ASABE (2005)
Total nitrogen at a given day – swine boar 200 kg		N_2O	kg N/kg dry manure	Entity Entry	0.07	Mean					ASABE (2005)
Total ammonia nitrogen in the manure – beef earthen lot	TAN	NH_3	kg NH_3/m^3	Entity Entry	0.1	Mean			0	0.02	ASABE (2005)

Data Element Name	Data Element Abbreviation/Symbol	Emission Type	Data Input Unit	Input Type	Estimated Value	Type of Estimate	Relative uncertainty Low (%)	Relative uncertainty High (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Total ammonia nitrogen in the manure – poultry, leghorn pullets	TAN	NH_3	kg NH_3/m^3	Entity Entry	0.85	Mean			0.66	1.04	ASABE (2005)
Total ammonia nitrogen in the manure – poultry, leghorn hen	TAN	NH_3	kg NH_3/m^3	Entity Entry	0.88	Mean			0.54	1.22	ASABE (2005)
Total ammonia nitrogen in the manure – poultry, broiler	TAN	NH_3	kg NH_3/m^3	Entity Entry	0.75	Mean					ASABE (2005)
Ammonia concentration in the liquid – dairy lagoon effluent	NH_3	NH_3	kg NH_3/m^3	Calculated	0.08	Mean					ASABE (2005)
Ammonia concentration in the liquid – dairy slurry (liquid)	NH_3	NH_3	kg NH_3/m^3	Calculated	0.14	Mean					ASABE (2005)
Ammonia concentration in the liquid – Swine Finisher-Slurry wet-dry feeders	NH_3	NH_3	kg NH_3/m^3	Calculated	0.5	Mean					ASABE (2005)
Ammonia concentration in the liquid – Swine Slurry storage-dry feeders	NH_3	NH_3	kg NH_3/m^3	Calculated	0.34	Mean			0.19	0.49	ASABE (2005)
Ammonia concentration in the liquid – Swine flush building	NH_3	NH_3	kg NH_3/m^3	Calculated	0.14	Mean					ASABE (2005)
Ammonia concentration in the liquid – Swine agitated solids and water	NH_3	NH_3	kg NH_3/m^3	Calculated	0.05	Mean					ASABE (2005)
Ammonia concentration in the liquid – Swine Lagoon surface water	NH_3	NH_3	kg NH_3/m^3	Calculated	0.04	Mean					ASABE (2005)
Ammonia concentration in the liquid – Swine Lagoon sludge	NH_3	NH_3	kg NH_3/m^3	Calculated	0.07	Mean					ASABE (2005)
Methane Conversion Factor (MCF) [a]– Dairy Cow	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Cattle	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Buffalo	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Market Swine	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Breeding Swine	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor [a] – Layer (Dry)	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Broiler	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Turkey	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Duck	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Sheep	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Goat	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Horse	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Mule/Ass	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)

Data Element Name	Data Element Abbreviation/Symbol	Emission Type	Data Input Unit	Input Type	Estimated Value	Type of Estimate	Relative uncertainty Low (%)	Relative uncertainty High (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Methane Conversion Factor[a] – Buffalo	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – In vessel manure composting	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Static pile manure composting	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Intensive windrow	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Methane Conversion Factor[a] – Passive windrow	MCF	CH_4	%	Default Entry			-30	30			IPCC (2006)
Maximum Methane Producing Capacities – Beef Replacement Heifers	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.33		-20	20			U.S. EPA (2011)
Maximum Methane Producing Capacities – Dairy Replacement Heifers	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.17		-20	20			U.S. EPA (2011)
Maximum Methane Producing Capacities – Mature Beef Cows	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.33		-20	20			U.S. EPA (2011)
Maximum Methane Producing Capacities – Steers (>500 lbs)	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.33		-20	20			U.S. EPA (2011)
Maximum Methane Producing Capacities – Stockers (All)	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.17		-20	20			U.S. EPA (2011)
Maximum Methane Producing Capacities – Cattle on Feed	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.33		-20	20			U.S. EPA (2011)
Maximum Methane Producing Capacities – Dairy Cow	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.24		-20	20			U.S. EPA (2011)
Maximum Methane Producing Capacities – Cattle	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.19		-20	20			U.S. EPA (2011)
Maximum Methane Producing Capacities – Buffalo[b]	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.1						IPCC (2006)
Maximum Methane Producing Capacities – Market Swine	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.48		-30	30			IPCC (2006)
Maximum Methane Producing Capacities – Breeding Swine	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.48		-30	30			IPCC (2006)
Maximum Methane Producing Capacities – Layer (dry)	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.39		-30	30			IPCC (2006)
Maximum Methane Producing Capacities – Layer (wet)	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.39		-30	30			IPCC (2006)
Maximum Methane Producing Capacities – Broiler	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.36		-30	30			IPCC (2006)

Data Element Name	Data Element Abbreviation/Symbol	Emission Type	Data Input Unit	Input Type	Estimated Value	Type of Estimate	Relative uncertainty Low (%)	Relative uncertainty High (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Maximum Methane Producing Capacities – Turkey	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.36		-30	30			IPCC (2006)
Maximum Methane Producing Capacities – Duck	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.36		-30	30			IPCC (2006)
Maximum Methane Producing Capacities – Sheep	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.19		-20	20			IPCC (2006)
Maximum Methane Producing Capacities – Feedlot sheep	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.36		-20	20			IPCC (2006)
Maximum Methane Producing Capacities – Goat	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.17		-30	30			IPCC (2006)
Maximum Methane Producing Capacities – Horse	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.3		-30	30			IPCC (2006)
Maximum Methane Producing Capacities – Mule/Ass	B_o	CH_4	m^3 CH_4/kg VS	Default Entry	0.33		-30	30			IPCC (2006)
Emission factor for the fraction of CH_4 produced that leaks from the anaerobic digester – Digesters with steel or lined concrete or fiberglass digesters with a gas holding system (egg shaped digesters) and monolithic construction	$EF_{CH4, leakage}$	CH_4	%	Default Entry	2.8						CDM (2012)
Emission factor for the fraction of CH_4 produced that leaks from the anaerobic digester – UASB type digesters with floating gas holders and no external water seal	$EF_{CH4, leakage}$	CH_4	%	Default Entry	5						CDM (2012)
Emission factor for the fraction of CH_4 produced that leaks from the anaerobic digester – Digesters with unlined concrete/ferrocement/brick masonry arched type gas holding section; monolithic fixed dome digesters	$EF_{CH4, leakage}$	CH_4	%	Default Entry	10						CDM (2012)
Emission factor for the fraction of CH_4 produced that leaks from the anaerobic digester – Other digester configurations	$EF_{CH4, leakage}$	CH_4	%	Default Entry	10						CDM (2012)
Temporary storage of liquid/slurry manure –N_2O emission factor[c]	EF_{N20}	N_2O	kg N_2O-N/kg N	Default Entry	0.005		-50	100			U.S. EPA (2011)
Long-term storage of solid manure –N_2O emission factor[c]	EF_{N20}	N_2O	kg N_2O-N/kg N	Default Entry	0.002		-50	100			U.S. EPA (2011)

Data Element Name	Data Element Abbreviation/Symbol	Emission Type	Data Input Unit	Input Type	Estimated Value	Type of Estimate	Relative uncertainty Low (%)	Relative uncertainty High (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Long-term storage of slurry manure – N_2O emission factor[c]	EF_{N20}	N_2O	kg N_2O-N/kg N	Default Entry	0.005		-50	100			U.S. EPA (2011)
Cattle and Swine Deep Bedding (Active Mix)- N_2O emission factor[c]	EF_{N20}	N_2O	kg N_2O-N/kg N	Default Entry	0.07						IPCC (2006)
Cattle and Swine Deep Bedding (No Mix)- N_2O emission factor[c]	EF_{N20}	N_2O	kg N_2O-N/kg N	Default Entry	0.01						IPCC (2006)
Pit Storage Below Animal Confinements- N_2O emission factor[c]	EF_{N20}	N_2O	kg N_2O-N/kg N	Default Entry	0.002						IPCC (2006)
Natural aeration aerobic lagoons – N_2O conversion factor[c]	EF_{N20}	N_2O	kg N_2O-N/kg N	Default Entry	0.01		-50	100			IPCC (2006)
Forced aeration aerobic lagoons – N_2O conversion factor[c]	EF_{N20}	N_2O	kg N_2O-N/kg N	Default Entry	0.005		-50	100			IPCC (2006)
N_2O emission factor for liquid storage – uncovered liquid manure with a crust[c]	EF_{N20}	N_2O	kg N_2O-N/kg N	Default Entry	0.8		-50	100			IPCC (2006)
N_2O emission factor for liquid storage – uncovered liquid manure without a crust[c]	EF_{N20}	N_2O	kg N_2O-N/kg N	Default Entry	0		-50	100			IPCC (2006)
N_2O emission factor for liquid storage – covered liquid manure[c]	EF_{N20}	N_2O	kg N_2O-N/kg N	Default Entry	0		-50	100			IPCC (2006)
Composting – Ammonia emission (loss) relative to total nitrogen in manure	EF_{NH3}	NH_3	kg NH_3-N/kg N	Default Entry	0.05						Hellebrand and Kalk (2000)
Manure Management – Multiple Sources – collection efficiency, covered storage (with or without crust)	η	CH_4	percentage	Default Entry	1						Sommer et al. (2004)
Manure Management – Multiple Sources – collection efficiency, uncovered storage with crust formation	η	CH_4	percentage	Default Entry	0						Sommer et al. (2004)
Manure Management – Multiple Sources – collection efficiency, uncovered storage without crust formation	η	CH_4	percentage	Default Entry	-0.40						Sommer et al. (2004)
Manure Management – Multiple Sources – Rate correcting factors (b_1)	b_1	CH_4	dimensionless	Default Entry	1						Sommer et al. (2004)
Manure Management – Multiple Sources – Rate correcting factors (b_2)	b_2	CH_4	dimensionless	Default Entry	0.01						Sommer et al. (2004)
Manure Management – Multiple Sources – Arrhenius parameter, cattle	A	CH_4	g CH_4 /kg VS/hr	Default Entry	43.33						Sommer et al. (2004)
Manure Management – Multiple Sources – Arrhenius parameter, swine	A	CH_4	g CH_4 /kg VS/hr	Default Entry	43.21						Sommer et al. (2004)

Data Element Name	Data Element Abbreviation/Symbol	Emission Type	Data Input Unit	Input Type	Estimated Value	Type of Estimate	Relative uncertainty Low (%)	Relative uncertainty High (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Potential methane yield of the manure cattle	$E_{CH4, pot -}$	CH_4	kg CH_4/kg VS	Default Entry	0.48						Sommer et al. (2004)
Potential methane yield of the manure - swine	$E_{CH4, pot}$	CH_4	kg CH_4/kg VS	Default Entry	0.5						Sommer et al. (2004)
Manure Management – Multiple Sources – Kinematic viscosity of air[e]	v	NH_3	m^2/s	Default Entry							White (1999)
Manure Management – Multiple Sources – Mass diffusivity of NH_3[e]	D	NH_3	m^2/s	Default Entry							Watson (1966) and Baker (1969)
Temporary stack and long-term stockpile – Resistance to mass transfer through the manure[e]	R_s	NH_3	s/m	Default Entry							Rotz et al. (2011)
Temporary stack and long-term stockpile – Resistance to mass transfer through the cover[e]	R_c	NH_3	s/m	Default Entry							Rotz et al. (2011)
Temporary stack and long-term stockpile – Ratio degradable volatile solids to total volatile solids - cattle liquid manure	VS_d/VS_T	CH_4	Unitless	Default Entry	0.46						Møller et al. (2004)
Temporary stack and long-term stockpile – Ratio degradable volatile solids to total volatile solids - swine liquid manure	VS_d/VS_T	CH_4	Unitless	Default Entry	0.89						Møller et al. (2004)
Temporary stack and long-term stockpile – Ratio Non-degradable volatile solids to total volatile solids - cattle liquid manure	VS_{nd}/VS_T	CH_4	Unitless	Default Entry	0.54						Møller et al. (2004)
Temporary stack and long-term stockpile – Ratio non-degradable volatile solids to total volatile solids – swine liquid manure	VS_{nd}/VS_T	CH_4	Unitless	Default Entry	0.11						Møller et al. (2004)
Solid-liquid separation – Efficiency of mechanical solid-liquid separation[e]		CH_4, N_2O, NH_3	Percent	Entity Entry							Ford and Fleming (2002)

[a] The values for methane conversion factor (MCF) vary depending on the temperature and the manure management system. IPCC (2006) provides estimated uncertainty ranges for these MCFs.

[b] There are no data for North America region; the data from Western Europe are used to calculate the estimation. There is no reported uncertainty for this adapted value.

[c] IPCC (2006) reports large uncertainties with default N_2O emission factors. The N_2O EF values vary depending on the animal species and temperature of the manure management system.

[d] Values for N_2O conversion factors are available for dairy cow, cattle, swine, and other animals and can be found in the chapter.

[e] Default values are available in the chapter.

Table 8-B-6: Forestry Uncertainty Table

Forestry Sub-Source Category	Data Element Name	Abbreviation/Symbol	Emission Type	Data Input Unit	Input Source	Statistic	Type of Statistic	Probability Distribution Type	Relative uncertainty Low (%)	Relative uncertainty High (%)	Confidence Level (%)	Effective Lower Limit	Effective Upper Limit	Data Source
Urban Forestry – Aerial Data Method	Tree Cover Percent		CO_2	%	Model Output									i-Tree Canopy
Urban Forestry – Aerial Data Method	Urban Area		CO_2	m^2	Entity Entry									
Urban Forestry – Aerial Data Method	Average Annual Carbon Sequestration		CO_2	kg $C/m^2/year$	Default Entry	2.8	mean		14.8	14.8				Nowak et al. (2013)
Urban Forestry – Aerial Data Method	Average Carbon Storage		CO_2	kg C/m^2	Default Entry	7.69	mean							Nowak et al. (2013)

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