Reducing climate policy risk:

Improving certainty and accuracy in the U.S. land use, land use change, and forestry greenhouse gas inventory

Technical Appendix

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1 Introduction

This project seeks to support ongoing improvements to the U.S. land use, land use change, and forestry (LULUCF) greenhouse gas (GHG) inventory by quantifying uncertainty from all equations and datasets using statistical methods, and estimating major omitted sources using literature review, and using this quantitative analysis to prioritize recommendations for research and data improvements.

Led by Emily McGlynn (University of California, Davis), the project consortium includes ClimateWorks Foundation, California Environmental Associates, Industrial Economics, and research fellows Kandice Harper and Serena Li. The research team has worked over the past year in collaboration with leading academics and federal experts that work directly on the NGHGI in order to compile the best available information on current inventory methods and data.

In the Technical Appendix, we present the quantitative methods used to estimate and attribute sources of uncertainty across the LULUCF chapter and agriculture soil management sections of the U.S. National Greenhouse Gas Inventory (NGHGI), as well as methods to quantify each identified omitted GHG flux. The Technical Appendix is organized by land category, covering (1) Forests, (2) Croplands and Grasslands, (3) Settlements, (4) Wetlands, and (5) Alaska, Hawaii, and U.S. Territories. Each land use type is then further segmented by NGHGHI flux categories. Each flux category in this document includes the following information:

- NGHGI Methods: Brief description of NGHGI quantification methods and key data sources
- Project Methods: Description of our methods for quantifying and attributing uncertainty across data inputs, equations, assumptions, and biases
- Results: Uncertainty attribution and/or omitted flux estimation results
- Discussion: Reflection on limitations of our methods and take-away points for developing recommendations based on results

For most of the Project Methods described below, we utilize uncertainty attribution methods to estimate how much each component of a calculation contributes to overall uncertainty. Wherever possible, we utilize the "contribution index" equation (Equation 1) from Ogle et al. (2003) to estimate uncertainty attribution from each element of uncertainty. Using this method requires recreating the GHG flux calculation in its entirety, and using either Monte Carlo or error propagation to estimate the 95% confidence interval of the GHG flux when holding each element of the calculation constant.

Equation 1: Contribution index (Ogle et al. 2003)

$$Index(i) = \frac{Range(full) - Range(i)}{\sum_{j=1}^{J} Range\,(full) - Range(j)} \times 100$$

Where:

i = 1,…,J represents each element of uncertainty;

Index(i) is the percentage contribution of element *i* to total uncertainty, measured by *Range(full)*;

Range(full) is the difference between the 97.5th quantile and the 2.5th quantile of the uncertainty range accounting for all elements of uncertainty, or the magnitude of the full 95% confidence interval; and

Range(i) is the magnitude of the 95% confidence interval holding element *i* constant.

For each flux category of the NGHGI we can estimate the percentage contribution of each element to total uncertainty, but we can also convert that percentage into million metric tons (MMT) CO_2e by multiplying the index value by the magnitude of the relevant 95% confidence interval, which enables us to compare elements' contributions to uncertainty across flux categories.

Every result table and original calculation in this document can also be found in the Spreadsheet Appendix, which provides additional information on calculation methods and equations.

2 Forests

2.1 Carbon stock change in forest biomass and deadwood

NGHGI METHODS

To quantify carbon fluxes in forest ecosystems, the NGHGI uses the stock-difference method, where the forest carbon flux in year *t* is calculated as the difference between carbon stocks in year *t* and year *t-1*. The NGHGI decomposes forest ecosystem carbon stocks into five distinct pools: (1) carbon in the aboveground biomass of live trees; (2) carbon in the belowground biomass of live trees; (3) carbon in dead wood, including both downed dead wood and standing dead trees; (4) carbon in litter; and (5) carbon in soil. Forest ecosystem carbon stocks are quantified using a Tier 3 method. Tree, downed dead wood, litter, and soil measurements are taken on U.S. forest land plots through the Forest Inventory and Analysis (FIA) program (USDA Forest Service 2018). These measurements are used to estimate carbon stocks using a suite of empirical and statistical models (e.g., Domke et al. 2011, 2016, 2017; Jenkins et al. 2003; Raile 1982; Woodall et al. 2011). Plot-level estimates are scaled to the entire U.S. forest area using post-stratified estimators (Bechtold and Patterson 2005). Since FIA measurements taken under the current sampling framework are not available for the entire NGHGI (2018) estimation timeframe (1990–2016), and because FIA plots are not re-measured annually, age transition and land-use change matrices are required to estimate annual carbon stock changes for the full NGHGI time period (Coulston et al. 2015; Wear and Coulston 2015; Woodall et al. 2015). Calculations are carried out separately for forests remaining forests (FRF), non-forest to forest conversion (NFF), and forest to non-forest conversion (FNF). Thus, the carbon stock changes quantified by the NGHGI for forest ecosystems account for both land-use change and forest dynamics (i.e., disturbance and growth). We describe each step of this method in more detail.

The first step is data collection at FIA plots. The FIA program uses three levels of sampling, denoted Phases 1, 2, and 3 (Bechtold and Patterson 2005). In Phase 1, imagery – historically aerial photography, but increasingly satellite imagery – is used to stratify the U.S. land base between forest and non-forest and by more detailed forest characteristics. In Phase 2 sampling, measurements are taken on a nationally distributed set of permanent field plots that have been established at a density of approximately 1 plot per 6,000 acres of the U.S. land base. The Forest Service collects many data for each Phase 2 plot that is forested. The most important tree-level data for the NGHGI include tree status (i.e., living or dead), species, height, diameter, cull, and decay class. Phase 3 sampling occurs on 1/16 of Phase 2 plots and includes additional forest ecosystem measurements, including those focused on downed dead wood, litter, and soils. In the eastern United States, each FIA field plot is generally re-measured once every 5 years on a rotating basis (i.e., roughly 20% of plots are measured each year). In the western United States, the measurement cycle is on the order of 10 years. The NGHGI uses only those FIA field measurements obtained under the nationally consistent plot design and sampling protocol that was introduced in 1998, with plot establishment and measurements commencing in the following years (Bechtold and Patterson 2005).

Since quantities calculated at plot level must be scaled to population level (e.g., total state or national forest area), the Phase 1 stratification is used as a variance reduction technique, and each FIA region is therefore permitted to determine the frequency and technique by which the stratification is performed (Bechtold and Patterson 2005). When a wall-to-wall remote sensing technique is applied, the entire land base is pixelated, with each pixel being assigned to one stratum. The Phase 1 stratification is performed without the use of ground-based data from the Phase 2 and Phase 3 FIA measurement plots. Each ground plot is assigned to one of the strata according to which pixel overlaps the plot center. In Texas, the stratification is based on canopy cover from the 2011 National Land Cover Database (NLCD; Homer et al. 2015).

FIA field plots in eastern states have completed at least two full measurement cycles, so carbon flux estimates are based on data from re-measured plots. For a small subset of western states or parts of states, a complete set of re-measurements is not yet available, necessitating the incorporation of theoretical modeling in the estimation process (Wear and Coulston 2015). Very few states still apply theoretical modeling as of the most recent NGHGI (2019). The framework used to quantify national forest carbon stock change, summarized here briefly, is described in Annex 3.13 of the NGHGI (2018) and the references therein. The overarching equation for the stock change calculation based on re-measurements (Annex 3.13 of NGHGI 2018; Wear and Coulston 2015) is reproduced here for clarity as Equation 2:

Equation 2: Forest carbon stock change (NGHGI 2018; Wear and Coulston 2015)

$$\Delta C_{t+s} = \sum_{d \in L} (A_{td} \cdot T_d \cdot \delta C_d)$$

Where:

ΔC_{t+s} is change in carbon stock between time t and time t+s, where s is the re-measurement period;

d are mutually exclusive land categories (e.g., FRF, NFF, FNF);

A_{td} is area by age class at time t for specified land category (1 x 26 vector);

T_d is age transition matrix for specified land category over the time step s (26 x 26 matrix); and

δC_d is carbon density change by age class for specified land category (26 x 1 vector).

The three matrices on the right hand side of Equation 2 are comprised of 26 age classes since carbon accumulation rates in forests vary strongly with age (Coulston et al. 2015). The 26 age classes are grouped by 5-year increments: 0 to <5 years, 5 to <10 years, … 120 to < 125 years, 125+ years (Coulston et al. 2015). Each element in the age transition matrix (T_d) represents the fraction of the forest area in the specified initial age class that transitions to the specified final age class over the time step; each column of T_d represents an initial age class, while each row of T_d represents a final age class. Application of the age transition matrix (T_d) to the area vector (A_{td}) serves to modify the age structure of the forest between time t and time t+s following observed historic trends. For forest conversion categories (FNF and NFF), T_d is simply the identity matrix. Stock changes delineated by carbon pool are estimated by applying a carbon-pool-specific carbon density change vector (δC_d). Each of the three matrices (A_{td}, T_d, and δC_d) is empirically derived at plot level from re-measurements. The three matrices in Equation 2 are individually expanded from plot to population level prior to multiplication.

Extrapolation from FIA plots to the total state or U.S. forest area makes use of the post-stratified estimators described by Bechtold and Patterson (2005). For example, to estimate state-level forest area, the plot-level estimates of forest proportion are averaged for each of the available strata; the strata means are then multiplied by the respective total state-level strata areas and summed. The variance calculations likewise take into account the various strata area weights (Bechtold and Patterson 2005), and these calculations underpin the sampling-based uncertainty reported by the NGHGI. The total 95% confidence interval for forest carbon flux reported in the NGHGI additionally includes model-based uncertainty, but the technique used to estimate model uncertainty is not described. The NGHGI assumes that the model-based and sampling-based uncertainties are independent and thus sums them together for total uncertainty of forest carbon flux estimates (Annex 3, sub-section 3.13 of NGHGI 2018).

PROJECT METHODS

To attribute uncertainty across the data, models, and estimation techniques of the NGHGI forest section, we replicated the national forest carbon flux estimation method for eastern Texas and then used Monte Carlo iterations to attribute percentage contribution for each "element of uncertainty" to the total 95% confidence interval for Texas forest carbon flux. Here, we present the methods applied to the calculations for eastern Texas, which focus on living tree biomass and standing dead trees for forest land remaining forest land (FRF). We provide the code and data used to develop these results in the Code Appendix.

We chose to focus on eastern Texas because replicating the methods for a single region was more tractable given time available, the complexity of the FIA data, and our available computational resources for running Monte Carlo simulations, which requires estimating carbon stocks 10,000 times for every FIA plot included in our analysis, for each uncertainty element. Texas forest land might be considered representative of forest land at the national scale given the diversity of forest types in Texas: productive timberland in the east and less dense woodlands in the west. We initially selected Texas as the basis of our analysis due to the east/west differences in measurement cycles and, therefore, carbon flux calculation methodologies that are applied in NGHGI (2018). However, in the most recent NGHGI (2019), the theoretical modeling approach is no longer applied to western Texas; instead, the estimation for western Texas is now based on re-measurements, as for eastern Texas. We therefore simplify our analytical framework for computational efficiency and base our calculations on only eastern Texas. Our analysis attempts to re-construct the estimation technique used in NGHGI (2018) based on the description of this technique that is given in NGHGI (2018), Woodall et al. (2015), and the references therein, using FIA data. We did not have access to the code used to develop the NGHGI values themselves, but given feedback from NGHGI experts and similarity of our results to NGHGI values we believe our calculation methods are valid.

The FIA plot data for Texas in comma-separated values (CSV) file format was obtained from the FIA DataMart (USDA Forest Service 2018). All analyses, including the Monte Carlo simulations, were performed using the R programming language (R Core Team 2018). We use data.table (Dowle and Srinivasan 2019) and truncnorm (Mersmann et al. 2018) R packages. Descriptions of the tables and variables available in the FIA Database for Phase 2 plots are given in Burrill et al. (2017).

The subplot condition change matrix (SUBP_COND_CHNG_MTRX table from the FIA Database) provides the basic underlying dataset for the calculations. For eastern Texas, we use only those data records corresponding to EVALID 481723. That is, we select the same data records used for eastern Texas that were used in the NGHGI (2018) analysis. This accounts for measurements on 3,778 FIA field plots in eastern Texas. In this dataset, time 1 ("previous") measurements span 2004–2012. Roughly 20% of plots were measured in each of the years 2008–2012, with only 0.2% (8 plots) measured before 2008 (1 plot in 2004, 3 plots in 2005, and 4 plots in 2007). Time 2 ("current") measurements span 2009–2017. Roughly 20% of plots were measured in each of the years 2013–2017, with <0.1% (2 plots) measured in 2009.

The generalized Equation 2 can be applied across land use and land use change categories. For example, carbon stock change estimates for FRF can be sub-divided into (1) undisturbed forest remaining undisturbed forest and (2) FRF that has experienced a disturbance, such as cutting, weather, insects, disease, and fire, with separate calculations possible for each disturbance type (Wear and Coulston 2015). In our eastern Texas analysis, the FRF category takes into account both undisturbed and disturbed forest categories, as long as the land use is classified as forest at both the previous and current time points; that is, we include in our FRF analysis all data records with the specified EVALID for which the current condition (CONDID) and the previous condition (PREVCOND) are both classified as accessible forest land (COND_STATUS_CD=1), as determined from the condition (COND) table. For this timeframe in eastern Texas, there are 2,242 re-measured plots that have at least one FRF zone. We obtain from the TREE table all tree records available for each of the PLOT–SUBP–CONDID–PREVCOND combinations in the filtered SUBP_COND_CHNG_MTRX dataset. For FRF, this includes trees measured in either or both of the current and previous time periods (total of 120,684 tree records).

We quantify aboveground and belowground (coarse root) biomass for all living (STATUSCD=1) and standing dead (STATUSCD=2 and STANDING_DEAD_CD=1) trees with diameter ≥ 1 inch. The biomass calculations differ depending on whether the tree is: (1) timber or woodland type; (2) living or standing dead; and (3) sapling (1.0 inch ≤ diameter < 5.0 inches) or non-sapling (diameter ≥ 5.0 inches). For timber type trees, FIA field crews measure diameter at breast height (DBH); for woodland type trees, FIA field crews measure diameter at root collar (DRC) and record the number of stems (WDLDSTEM attribute in the TREE table). Tree type is identified using the DIAHTCD attribute in the TREE table (DIAHTCD=1 for timber trees, DIAHTCD=2 for woodland trees). For the eastern Texas FRF analysis, nearly all tree records correspond to the timber type: 91,083 non-sapling living timber (75.5% of all trees); 25,211 sapling living timber (20.9%); 4,246 non-sapling standing dead timber (3.5%); 123 sapling standing dead timber (0.1%); 16 non-sapling living woodland (<0.1%); and 5 sapling living woodland (<0.1%).

The equations used for the tree-level biomass calculations are available in Woodall et al. (2011). Biomass estimation for living non-sapling (diameter ≥ 5.0 inches) timber trees follows the component ratio method (Woodall et al. 2011): (1) gross volume is estimated as a function of measured diameter and height through application of species-specific regression coefficients (some volume equations make use of additional variables, but the equations applied to the tree species found in eastern Texas rely only upon measurements of diameter and height); (2) sound volume is estimated from gross volume by subtracting the observed cull (rotten and missing pieces); (3) bole biomass is calculated from sound volume through application of species-specific wood and bark specific gravities and a parameter defining bark as a percentage of wood volume; and (4) biomass by component is estimated through modified application of the diameter-based regression equations from Jenkins et al. (2003) and, for stumps, the equations from Raile (1982). Biomass estimation for living non-sapling woodland trees follows a similar method (Woodall et al. 2011), with only slight modification (e.g., stump biomass is not estimated). The volume coefficients for woodland species vary according to the number of stems (WDLDSTEM attribute in TREE table). Biomass estimation for living saplings is largely based on the regression equations from Jenkins et al. (2003), but includes application of a "sapling adjustment factor" (Heath et al. 2009). Tree species is defined by the species code (SPCD) in the TREE table.

The volume coefficients are available in Woodall et al. (2011). The other coefficients needed to calculate living tree biomass are available in the REF_SPECIES table from the FIA Database: stump volume coefficients from Raile (1982); specific gravities and bark percentages compiled by Miles and Smith (2009); coefficients for calculating diameter-based total aboveground biomass and biomass component ratios from Jenkins et al. (2003; 2004); and sapling adjustment factors from Heath et al. (2009).

Domke et al. (2011) describe the updated method for quantifying standing dead biomass for trees with diameter ≥ 5.0 inches, which takes into account reduced density and structural loss associated with decay. The degree of decay for each standing dead tree is defined by the decay code (DECAYCD, possible values 1–5) available in the TREE table. Domke et al. (2011) provide density reduction factors for each of the five decay codes for two tree species: quaking aspen and douglas-fir. We apply the quaking aspen density reduction factors to all hardwood trees (SPGRPCD=1–24) and the douglas-fir density reduction factors to all softwood trees (SPGRPCD=25–48). The calculation of biomass in standing dead saplings identically follows the calculation of biomass in living saplings, with no density or structural loss adjustments applied. For both aboveground and belowground components for living and standing dead trees of all sizes and tree types, the mass of carbon is calculated as 50% of the dry biomass, following IPCC (2006). These calculations provide the carbon mass (pounds C tree^{-1}) for each tree in the dataset.

For each tree record, tree-level carbon (pounds C tree^{-1}) is multiplied by TPA_UNADJ (trees acre^{-1}) to obtain the plot-level carbon density (pounds C acre^{-1}) represented by the tree. Separately for the current and previous time periods, the tree-based carbon densities are aggregated over all FRF area on the plot. In our calculation, aggregation is done over all FRF area on the plot, rather than by age class (e.g., Equation 2), to avoid unnecessary computational expense in the Monte Carlo analysis, details of which are provided below. For each plot, the previous period density is subtracted from the current period density, and the difference is divided by the plot-level re-measurement period in years (REMPER attribute from the PLOT table). In cases where there are no trees available on the plot for one of the time periods (e.g., non-stocked plots), the carbon density for that time period is simply zero pounds C acre^{-1}. For each plot, this process gives the annual carbon density change (pounds C acre^{-1} year^{-1}).

We limit our carbon stock estimation to aboveground and belowground biomass in living and standing dead trees with diameter ≥ 1.0 inch. We do not include estimation of carbon in downed dead wood or understory vegetation to simplify the analysis.

We use Monte Carlo analyses to estimate uncertainty of carbon stock change estimates in eastern Texas. We apply 10,000 Monte Carlo iterations to the derivation of the plot-level carbon density changes for the 2,236 FRF plots in eastern Texas that have trees in either or both of the measurement periods. To estimate the fraction of uncertainty associated with nine different model parameters or parameter groups, we repeat the full set of 10,000 iterations ten times (variously allowing one parameter group to vary while all other parameters are held to their mean values plus one set of iterations where all parameters are allowed to vary). Note that this method diverges from Equation 1 described above, and from methods used in the rest of this report, wherein the uncertainty contribution index for element *i* is determined by holding element *i* constant and varying all other elements. We use this modified approach for forest biomass due to the complexity of the calculations, which results in compensating variation when only holding one element constant, and makes interpretation of results difficult. Each Monte Carlo simulation results in 10,000 iterates of carbon density change (units: pounds C acre^{-1} y^{-1}) for each of the 2,236 eastern Texas plots. Note that for each Monte Carlo iteration, the same parameters are used for both measurement periods.

We apply the output of the Monte Carlo simulation in which all parameters are allowed to vary to equations 1–6 from Ogle et al. (2010) to estimate the total annual carbon stock change for eastern Texas and the associated total modeling and sampling errors. The total eastern Texas carbon stock change for any individual Monte Carlo iterate (units: pounds C y^{-1}) was calculated by multiplying, for each plot, the plot-level stock density change for that iterate (units: pounds C acre^{-1} y^{-1}) by that plot's area weight (units: acres; derivation described below) and then summing this product over all 2,242 plots (equation 1 of Ogle et al. 2010). The 6 plots in eastern Texas that are classified as FRF but lack trees in both measurement periods are taken into account in these calculations; for application of Ogle et al. (2010) equation 1, all 10,000 iterates assume a stock density change of zero pounds C acre^{-1} y^{-1} for these 6 plots. This process was repeated for each of the 10,000 Monte Carlo iterates. The mean annual carbon stock change for eastern Texas (units: pounds C y^{-1}) was calculated by taking the average of the 10,000 iterates of eastern Texas carbon stock change (equation 2 of Ogle et al. 2010).

For stratification, eastern Texas is divided into three non-overlapping geographic areas known as "estimation units" (ESTN_UNIT) in the FIA Database: (1) National Forest Service (NFS) land, which accounts for 2.9% of the area of eastern Texas; (2) Southeast Texas, excluding NFS land, which accounts for 53.2% of the area of eastern Texas; and (3) Northeast Texas, excluding NFS land, which accounts for 43.9% of the area of eastern Texas. In the FIA Database, each estimation unit is stratified into canopy cover bins, following the 2011 National Land Cover Database (Homer et al. 2015). The NFS land is divided into two strata: (1) 37.5% of total area has 0–98% canopy cover and (2) 62.5% has 99–100% canopy cover. Southeast Texas is divided into four strata: (1) 28.8% of total area has 0–10% canopy cover; (2) 18.1% has 11–47% canopy cover; (3) 14.2% has 48–84% canopy cover; and (4) 39.0% has 85–100% canopy cover. Northeast Texas is divided into three strata: (1) 43.6% of total area has 0–47% canopy cover; (2) 17.7% has 48–84% canopy cover; and (3) 38.7% has 85–100% canopy cover. Overall, there are nine estimation unit–stratum combinations in eastern Texas, and each plot in eastern Texas is assigned to one of these nine estimation unit–stratum combinations (henceforth, simply referred to as "stratum").

In the equations of Ogle et al. (2010), the area weight assigned to each plot indicates the number of acres of FRF area in all of eastern Texas that is represented by that plot. The area weight for each plot depends both on the stratum to which the plot belongs and on the size of the FRF area on that plot. The total area of FRF in each stratum is reported in FIA: (1) 218,413 acres of NFS land with 0–98% canopy cover; (2) 397,919 acres of NFS land with 99–100% canopy cover; (3) 46,004 acres in Southeast Texas with 0–10% canopy cover; (4) 523,504 acres in Southeast Texas with 11–47% canopy cover; (5) 1,101,242 acres in Southeast Texas with 48–84% canopy cover; (6) 4,405,042 acres in Southeast Texas with 85–100% canopy cover; (7) 356,070 acres in Northeast Texas with 0–47% canopy cover; (8) 1,112,189 acres in Northeast Texas with 48–84% canopy cover; and (9) 3,579,941 acres in Northeast Texas with 85–100% canopy cover. Within a stratum, each plot in the stratum is assigned an area weight in proportion to the size of the plot's FRF area, as determined by the subplot type proportion change

(SUBPTYP_PROP_CHNG) attribute of the SUBP_COND_CHNG_MTRX table, which details the proportion of the subplot that remains in the same land use category or changes category over the re-measurement period. Area weights were calculated for each of the 2,242 eastern Texas plots that had any FRF area over the re-measurement period.

The model-based variance was calculated using equation 3 of Ogle et al. (2010), and the sample-based variance was calculated using equations 4 and 5 of Ogle et al. (2010) using a method that accounts for stratification of the land base. The total variance is calculated by summing the model and sample variances (equation 6 of Ogle et al. 2010), which follows the practice of the NGHGI, in which the model and sample variances are assumed to be independent (Annex 3, sub-section 3.13 of NGHGI 2018). We use this combined variance to derive the total 95% confidence interval for eastern Texas carbon stock change associated with living and standing dead tree biomass.

The plot-level carbon density changes and area weights are derived from re-measurements at each plot. Only 20% of eastern Texas ground plots are measured each year in the rotating panel design used by FIA, which means that it takes on the order of five years to measure the full set of plots. For eastern Texas, the mean re-measurement period for our dataset is 5.4 years. Thus, our estimate of annual carbon stock change for all of eastern Texas is not specific to a certain year, but instead is assumed to be representative of average annual trends for the region.

We use the additional nine Monte Carlo simulations to probe the contribution to uncertainty from various model parameters. For each of these simulations, one of nine different model parameters or parameter groups is allowed to vary while all other parameters are held to their mean values. For each of these nine Monte Carlo simulations, we apply equations 1–3 of Ogle et al. (2010) to estimate the model variance based on variation of a single parameter or parameter group.

Considering the nine simulations where only one parameter is allowed to vary, the sum of the individual model variances for these nine simulations is 0.8018 [MMT CO_2]^2. This is nearly identical to the model variance from the simulation where all parameters are allowed to vary simultaneously: 0.8013 [MMT CO_2]^2. We derived the percentage contribution to total uncertainty for each of the nine model parameter groups as: 100 x (scaled individual model variance) / total variance, where total variance is the sum of the model and sample variances from the simulation where all parameters are allowed to vary. The percentage contribution to total uncertainty from the sample error is calculated as: 100 x sample variance / total variance. The percentage contributions to uncertainty for the nine model parameter groups and the sampling error sum to 100%.

The nine parameters groups we assess are briefly described below. More information is available in Woodall et al. (2011) and references therein, notably: Domke et al. (2011), Heath et al. (2009), Jenkins et al. (2003, 2004), Miles and Smith (2009), and Raile (1982).

(1) **Volume coefficients**: Used to calculate gross bole volume from measurements of height and diameter. Directly applied only to trees with diameter ≥ 5.0 inches. Considering the full set of trees in this eastern Texas dataset, 81 different sets of species-specific volume coefficients are applied. Two coefficients are reported for each timber tree species in this dataset. Six coefficients are reported for each woodland tree species.

(2) **Wood and bark specific gravities**: Used to convert bole volume to biomass. Directly applied only to trees with diameter ≥ 5.0 inches. Considering the full set of trees in this eastern Texas dataset, 30 different values of species-specific wood specific gravity are applied and 27 different values of species-specific bark specific gravity are applied.
(3) **Bark as a percentage of wood volume**: Used to convert bole volume to biomass. Directly applied only to trees with diameter ≥ 5.0 inches. Considering the full set of trees in the eastern Texas dataset, 20 different values of species-specific bark percentage are applied.
(4) **Stump volume coefficients**: Used to quantify the volume of the tree stump from measured diameter. Directly applied only to timber trees with diameter ≥ 5.0 inches. Considering the full set of trees in this eastern Texas dataset, 6 different sets of species group-specific stump volume coefficients are applied.
(5) **Total aboveground biomass** following Jenkins et al. (2003): Total aboveground biomass calculated from measured diameter using regression equations. Used to estimate an adjustment factor applied in the Component Ratio Method. Considering the full set of trees in this eastern Texas dataset, 7 different sets of species group-specific coefficients are applied. A set of coefficients includes 2 coefficients. When this parameter is allowed to vary, the prescribed variance (error bar) is applied directly to the calculated diameter-dependent biomass for each tree, rather than on the coefficients used to calculate the biomass (see description in Table T-1).
(6) **Component ratio coefficients:** Used in calculation of component ratios (i.e., ratio of tree component biomass to total aboveground biomass) following diameter-dependent regression equations of Jenkins et al. (2003). Two different sets of component ratio coefficients are applied (1 set for all hardwoods and 1 set for all softwoods). For timber trees with diameter ≥ 5.0 inches, a set of coefficients includes 8 coefficients: 2 each for foliage, coarse roots, stem wood, and stem bark. For woodland trees and saplings, a set of coefficients includes 4 coefficients: 2 each for foliage and coarse roots.
(7) **Sapling adjustment factor**: Used only for saplings to account for differences in the volume-based biomass estimation method of the Component Ratio Method and the Jenkins et al. (2003) diameter-based regression equations for biomass estimation. For the eastern Texas dataset, 22 different values of species group-specific sapling adjustment factors are applied.
(8) **Density reduction factor**: Scaling factor used to account for reduced density from decay of standing dead trees. For the eastern Texas dataset, 10 different values of density reduction factor are applied (depending on degree of decay and whether tree is hardwood or softwood).
(9) **Structural loss adjustment factors**: Scaling factor used to account for structural loss of standing dead trees. For the eastern Texas dataset, 5 different sets of structural loss adjustment factors are applied (depending on degree of decay of the tree).

The distribution type and coefficient of variation (standard deviation as a percentage of the mean) assigned to each of the variable parameters are summarized in Table T-1. Parameters for which a literature-based or empirically derived estimate of the coefficient of variation could not be developed (i.e., volume coefficients, stump volume coefficients, and structural loss adjustment factors) were assigned a coefficient of variation of 10%, which matches the magnitude of the literature or empirically based coefficients of variation for many of the other parameters. In the Discussion section, we provide the results of a sensitivity analysis focused on the coefficient of variation prescribed for the volume coefficients.

In our computational framework, the random deviates of any variable parameter in a Monte Carlo simulation are not separately generated for each tree, but instead are generated around each available mean value of the parameter. In other words, all trees that are assigned the same mean value of a given parameter when that parameter is not allowed to vary are likewise assigned the same 10,000 iterates of that parameter when that parameter is allowed to vary. (The total aboveground biomass based on Jenkins et al. (2003) is an exception to this framework, as described in Table T-1.) This framework was selected for its computational efficiency and mimics the imposition of a high degree of positive covariance between trees of the same species or species group and also between the two time periods. However, this framework might lead to an underestimate of model uncertainty. Furthermore, we assume independence of all parameters, even within parameter groups, recognizing that this might upwardly bias our model uncertainty estimate.

We restrict the allowed values of some parameters by applying a truncated normal distribution; for example, we do not allow specific gravities to be negative (Table T-1). We impose only one other restriction in the Monte Carlo simulations: for each Monte Carlo iteration of component ratio coefficients: (1) if the resulting foliage ratio + stem ratio + bark ratio < 0.6, then we scale up each of these ratios so that the sum is 0.6 or (2) if the resulting foliage ratio + stem ratio + bark ratio > 0.9, then we scale down each of these ratios so that the sum is 0.9. We institute these thresholds in order to force the branch ratio to be in the range 0.1–0.4 (because the branch ratio is the residual of 1 - (stem ratio + bark ratio + foliage ratio) in Jenkins et al. (2003)). This restriction is only applied for timber trees with diameter ≥ 5.0 inches since it is only these trees for which ratios are calculated for all of the components.

Table T-1: Input parameters for contribution index analysis of forest biomass

Group number	Variable parameter(s)	Probability distribution	Coefficient of variation (%) [a]
1	Bole gross volume coefficients	Normal	10%
2	Wood and bark specific gravities	Truncated normal with lower limit of 0	10% [b]
3	Bark as a percentage of wood volume	Truncated normal with lower limit of 0	5% [c]
4	Stump volume coefficients	Normal	10%
5	Total aboveground biomass based on Jenkins et al. (2003)	Truncated normal with lower limit of 0	[d]
6	Component ratio coefficients	Normal	10% [e]
7	Sapling adjustment factor	Truncated normal with lower limit of 0	30% [f]
8	Density reduction factor	Truncated normal with lower limit of 0 and upper limit of 1	4% [g]
9	Structural loss adjustment	Truncated normal with lower limit of 0 and upper limit of 1	10%

a) Coefficient of variation is the standard deviation of the parameter as a percentage of the parameter mean.

b) Forest Products Laboratory (2010).

c) Estimated from 95% confidence intervals for bark as a percentage of wood volume for five different species given in Marden et al. (1975).

d) Table 5 of Jenkins et al. (2003) provides the 10th and 90th percentiles of the percentage of predicated biomass for each of 10 species groups (7 of which are present in the eastern Texas dataset). For each of the 7 species groups, we calculated the mean of the absolute values of the 10th and 90th percentiles and, from this, derived the standard deviation of the percentage of predicted biomass. For each tree in the species group, we applied this standard deviation in the generation of the 10,000 deviates of total aboveground biomass for each tree.

e) Coefficient variance was derived from summary statistics in tables 6 and 7 from Jenkins et al. (2003), using the parameter variance equation for linear regression with homoscedastic errors, taking the natural log of regression equation.

f) For all 852 trees in the eastern Texas dataset in the current measurement period that have diameter = 5.0 inches, we calculated the sapling adjustment factor by dividing the biomass based on the Component Ratio Method by that based on the method of Jenkins et al. (2003) (see Heath et al. 2009). We grouped the trees into species groups according to Table 3 of Heath et al. (2009) and estimated the mean and standard deviation of the sapling adjustment factors for each species group. We estimated the coefficient of variation for each species group; the mean of these coefficients of variation is about 30%.
g) Estimated from data in Table 6 of Harmon et al. (2011).

The NGHGI (2018) reports for 2016 a national total net sequestration of 420.2 MMT CO_2 from aboveground biomass (315.3 MMT CO_2), belowground biomass (65.7 MMT CO_2), and dead wood (39.2 MMT CO_2). These figures include both understory vegetation and downed dead wood, which we do not include in our analysis. To estimate the 95% confidence interval for national forest carbon stock change, we calculate for the percentage error for the eastern Texas analysis (100 x [0.5 x range of 95% confidence interval for eastern Texas] / mean carbon stock change for eastern Texas) and then apply this percentage error to the national mean carbon stock change reported by the NGHGI (2018). We quantify the contribution to uncertainty in units of MMT CO_2 for each of the nine model parameters and the sampling error by multiplying the percentage contribution to uncertainty for each uncertainty element by the range of the 95% confidence interval (97.5th percentile minus 2.5th percentile) for national carbon stock change. We report our results in aggregate across living tree biomass and standing dead tree carbon pools.

RESULTS

We estimate a net sequestration in aboveground and belowground living tree biomass and standing dead trees for eastern Texas of 5.3 MMT CO_2. This corresponds to the order of magnitude for 2016 (~2 MMT CO_2) suggested by the reported change in aboveground biomass for live trees in eastern Texas (Dooley 2018); we expect some discrepancy based on the differences in carbon pools considered (Dooley (2018) does not consider belowground biomass or standing dead trees) and the mis-match in years between our analysis and the Dooley (2018) analysis. As noted above, our analysis is not specific to one year but rather is an average over all available measurement years. Based on the Monte Carlo analysis where all parameters are allowed to vary, we estimate a model variance of 0.80 [MMT CO_2]^2, a sample variance of 2.55 [MMT CO_2]^2, and a total combined variance of 3.35 [MMT CO_2]^2. The 95% confidence interval for eastern Texas carbon stock change associated with living and dead tree biomass is -8.9 MMT CO_2 to -1.7 MMT CO_2, where negative values indicate sequestration. The total percentage error for eastern Texas (100 x [0.5 x range of 95% confidence interval] / mean carbon stock change) is 67.9%.

The 95% confidence interval for the national carbon stock change, calculated by applying the percentage error from eastern Texas to the national mean carbon stock change (-420.2 MMT CO_2) reported by the NGHGI (2018), is -705.6 MMT CO_2 to -134.8 MMT CO_2, accounting only for changes in the living tree biomass and standing dead tree carbon pools. In the Discussion section, we discuss the appropriateness of applying the percentage error derived for eastern Texas to the estimation of the total national 95% confidence interval.

The contributions to uncertainty for the nine model parameters and sample error are shown in Table T-2. The total contribution to uncertainty for this forest ecosystem carbon pool is 571 MMT CO_2. The sample error is the dominant contributor to uncertainty for this carbon pool. Among the model parameters, the volume coefficients and specific gravities make the largest contributions to uncertainty, followed by the biomass component ratio coefficients, sapling adjustment factor, and total aboveground biomass based on the allometric equations of Jenkins et al. (2003). Negligible uncertainty is contributed by bark as a percentage of wood volume, stump volume coefficients, density reduction factors, and structural loss adjustment factors.

Table T-2: RESULTS - Contributions to uncertainty for aboveground, belowground, and standing dead biomass, scaled to national level

Uncertainty element	Contribution to uncertainty (%)	Contribution to uncertainty (MMT CO_2e)
Sample error	76.1%	434.3
Bole gross volume coefficients	13.6%	77.7
Wood and bark specific gravities	9.5%	54.2
Bark as a percentage of wood volume	0.0%	0.2
Stump volume coefficients	0.0%	0.0
Total aboveground biomass based on Jenkins et al. (2003)	0.1%	0.7
Component ratio coefficients	0.4%	2.2
Sapling adjustment factor	0.3%	1.6
Density reduction factor	0.0%	0.0
Structural loss adjustment	0.0%	0.1

The NGHGI (2018) reports the 95% confidence interval for the sum of carbon stock changes from forest ecosystems for FRF for the United States (-818.7 MMT CO_2 to -324.7 MMT CO_2), but does not report the confidence intervals by forest carbon pool. Combining the results of our eastern Texas-based analyses for living tree biomass and standing dead trees (this section), litter (Section 2.2), and soil (Section 2.3), we find a percentage error of 53.3% for FRF, which is similar in magnitude to that reported by the NGHGI (2018): 43.2%. Applying our percentage error to the national mean net carbon stock change for 2016 for all forest ecosystem carbon pools (-571.6 MMT CO_2) reported by NGHGI (2018), we estimate a 95% confidence interval of -876.4 MMT CO_2 to -266.8 MMT CO_2, which compares well to that reported by NGHGI (2018), providing confidence in our overall estimate of uncertainty.

DISCUSSION

For our uncertainty analysis of carbon stock changes in aboveground and belowground living tree biomass and standing dead trees, we have attempted to re-create the carbon estimation framework used by the NGHGI (2018) insofar as we understand it from the descriptions provided in NGHGI (2018), Woodall et al. (2015), and the references therein. We have introduced some simplifications; for example, we do not consider forest age class, and we do not attempt to estimate the carbon stock changes in eastern Texas for a given year. Instead, we assume that carbon stock changes estimated from the re-measurements are representative of average annual trends for the region. Our estimation does not account for any nuances in the NGHGI estimation framework that are not specified in the methodological description provided in the NGHGI (2018). Furthermore, in light of the computationally intensive nature of the Monte Carlo framework that we use to estimate uncertainty and contributions to uncertainty from individual uncertainty elements, it was necessary to choose a subset of FIA ground plots as the input to our carbon model, as using the full set of national ground plots would have been intractable given available computational resources.

As described previously, we initially chose to analyze Texas because of the different calculation methodologies applied to the eastern and western parts of the state; however, because a full set of re-measurements are now available in western Texas and are used in the most recent NGHGI (2019) estimates, we chose to focus our efforts on only eastern Texas as a tractable subset of ground plots. Using our computational framework applied to the re-measured FIA ground plots in eastern Texas, we calculate a mean annual sequestration rate for eastern Texas FRF as 1.11 metric tons CO_2 [ha of FRF land]$^{-1}$, taking into account carbon sequestration associated with aboveground and belowground living tree biomass and standing dead trees. This is the same order of magnitude as the national mean sequestration rate for 2016 for FRF: 1.44 metric tons CO_2 [ha of FRF land]$^{-1}$. The national estimate additionally accounts for downed dead wood and understory vegetation, which is not included in our estimate for eastern Texas. Assuming that downed dead wood and understory vegetation in eastern Texas sequester carbon over this time period, then the estimated sequestration rate for eastern Texas is likely an underestimate. The comparable mean sequestration rate between eastern Texas and the United States is further evidence that eastern Texas is a representative region for national forest carbon flux.

Our forest carbon model is consistent with that used for the full United States, but the species distribution of the trees in the dataset is specific to eastern Texas. The variances of the model parameters, when based on literature, are likewise specific to that mix of trees (see Table T-1 for sources and assumptions on parameter variance). For our uncertainty analysis, we are most interested in ranking the various uncertainty elements in terms of their contribution to total uncertainty. Given that the rankings of the various parameter contributions are so pronounced (56.8% of model uncertainty is associated with the volume coefficients and 39.7% with specific gravities), it is not likely that a different species distribution would significantly alter the rankings.

As shown in the Results section, the total relative uncertainty, including both model and sample errors, that we calculate for eastern Texas FRF (53.3%, accounting for uncertainty associated with the estimation of carbon stock changes for aboveground and belowground biomass in living and standing dead trees, litter, and soil) compares well to that at the national level (43.2%) reported by the NGHGI (2018). Again, the national estimate additionally accounts for uncertainty associated with estimating carbon stock changes in downed dead wood and understory vegetation. The similarity in the total percentage uncertainties for eastern Texas and the United States suggests that eastern Texas uncertainty is representative of forest carbon uncertainty in the United States and it is therefore reasonable to apply the percentage error estimated for eastern Texas in our analysis to derive the 95% confidence interval for the United States. Importantly, our method for estimating uncertainties for litter and soil carbon fluxes required assumptions in assigning the covariance in carbon stocks between the two time points, with the result being that we indirectly set the variance of the carbon flux by assumption. If we double the assumed variances for both the litter and soil carbon fluxes, the total percentage uncertainty for eastern Texas FRF increases to 60.6%. Quadrupling these variances results in a total percentage uncertainty of 73.0%. Thus, the total percentage uncertainty for eastern Texas, even under these strong increases in uncertainty for the litter and soil carbon fluxes, still matches the order of magnitude of the national uncertainty.

Our contribution analysis finds that the coefficients used to calculate gross bole volume from measured height and diameter (for trees with diameter ≥ 5.0 inches) provide the largest contribution to modeling uncertainty for this carbon pool (aboveground and belowground biomass of living and standing dead trees) and provide the second largest contribution to uncertainty for this pool when sampling error is also considered. Because of a lack of information regarding the magnitude of this error bar, we assigned a generic coefficient of variation of 10% for these parameters, which is in line with the coefficients of variation assigned to many of the other modeling parameters (Table T-1). However, due to the importance of this parameter in terms of uncertainty contribution, we performed additional Monte Carlo simulations to determine how the magnitude of this error bar affects the overall uncertainty estimation and contribution analysis.

Test simulations show that the ranking of the model parameters in terms of uncertainty contribution is consistent between simulations using 500 iterations and those using 10,000 iterations, with only slight differences in the percentage contributions. For example, the simulations using 10,000 iterations suggest that the volume coefficients account for 56.8% of model error and the specific gravities account for 39.7% of model error; the simulations using 500 iterations suggest contributions of 53.9% and 42.3% for the volume coefficients and specific gravities, respectively. Because we are predominantly interested in how the error bar assigned to the volume coefficients affects the ranking of the model parameters in terms of uncertainty contribution, we base our sensitivity analysis on Monte Carlo simulations that use 500 iterations for the benefit of computational efficiency.

In these sensitivity simulations, only the coefficient of variation for the volume coefficients is modified relative to the main set of Monte Carlo simulations (in addition to the smaller number of iterations used). We run sets of simulations variously applying a coefficient of variation to the volume coefficients of 5%, 10% (as in the main set of simulations in the Results section), and 20%. To maintain consistency among the sensitivity simulations, we re-ran the main uncertainty simulations (i.e., 10% coefficient of variation as presented in the Results section) using 500 iterations.

For the 500-iterate simulations, the sum of the model variances for the simulations where only one parameter varies is greater than the total model variance derived from the Monte Carlo simulation where all parameters vary. For each set of simulations, we divided the total model variance derived from the Monte Carlo simulation where all parameters vary by the sum of the nine individual model variances to estimate a scaling factor for the individual model variances. The scaling factors are: (1) 0.860 for the analysis that assigns a coefficient of variation of 5%; (2) 0.913 for the analysis that assigns a coefficient of variation of 10%; and (3) 0.986 for the analysis that assigns a coefficient of variation of 20%. For each set of simulations, we derived the percentage contribution to total uncertainty for each of the nine model parameter groups as: 100 x (scaled individual model variance) / total variance, where total variance is the sum of the model and sample variances from the simulation where all parameters are allowed to vary. The percentage contributions to uncertainty for the nine model parameter groups and the sampling error sum to 100%.

The results of this sensitivity analysis (Table T-3) show that the magnitude of the error bar applied to the volume coefficients has a significant impact (1) on the overall 95% confidence interval for this aggregated forest carbon pool and (2) on the magnitude of the uncertainty contribution from the volume coefficients. The error bar applied to the volume coefficients also affects the ranking of the various uncertainty elements in terms of percentage contribution to uncertainty. For the uncertainty analysis in which the coefficient of variation for the volume coefficients is assigned as 10%, error associated with the volume coefficients accounts for 53.9% of modeling uncertainty, followed in importance by the wood and bark specific gravities (42.3%) and the component ratio coefficients (1.7%). When a coefficient of variation of 5% is applied, the contributions to modeling uncertainty are: wood and bark specific gravities (71.1%), volume coefficients (22.6%), and component ratio coefficients (2.9%). When a coefficient of variation of 20% is applied, the contributions to modeling uncertainty are: volume coefficients (82.4%), wood and bark specific gravities (16.2%), and component ratio coefficients (0.7%). Volume coefficient contribution at 20% coefficient of variation still does not overtake sampling error contribution, which is still nearly twice as large as volume coefficient contribution.

Table T-3: Sensitivity of uncertainty results to error bar used for volume coefficients

Coefficient of variation for volume coefficients (%)	Contribution of volume coefficient error to total uncertainty for this carbon pool (%)	Uncertainty contribution from volume coefficients (MMT CO_2)	95% confidence interval for United States		
			Lower bound (MMT CO_2)	Upper bound (MMT CO_2)	95% error bar, percentage of mean (%)
5%	3.2%	16.9	-687.7	-152.7	63.7
10% [a]	12.1%	68.1	-701.9	-138.5	67.0
20%	37.1%	248.1	-754.8	-85.6	79.6

a) These results correspond to the main uncertainty analysis presented in the Results section, but have been derived from simulations run with 500 iterations rather than 10,000 iterations in order to maintain consistency with the other sensitivity simulations. The reduction from 10,000 iterations to 500 iterations in the Monte Carlo simulation has little impact on the estimated 95% confidence interval for the United States. The percentage contribution to total uncertainty for this carbon pool from volume coefficient error is slightly lower when based on the simulations using 500 iterations (12.1%) than when based on the simulations using 10,000 iterations (13.6%), resulting in a lower uncertainty contribution in terms of MMT CO_2 (68.1 MMT CO_2 here compared to 77.7 MMT CO_2 as in Table T-2). The volume coefficient ranks as the highest contributor to uncertainty among all model parameters regardless of whether 500 or 10,000 iterations are applied.

In our analysis, we do not capture all errors associated with the estimation of carbon stock change in this aggregated forest carbon pool (aboveground and belowground carbon in living and standing dead trees). For example, we do not consider errors associated with (among others): (1) the stratification applied to the land base; (2) measurement errors; (3) expansion factors, such as the TPA_UNADJ variable from the FIA Database; or (4) model structure (e.g., the impact on carbon stock estimates associated with the transition to the volume-based Component Ratio Method for tree biomass from the allometric regression models of Jenkins et al. (2003) is considered by Domke et al. (2012)). However, an advantage of our analysis presented here is that we use a consistent approach across LULUCF sub-sectors (i.e., where possible, Monte Carlo simulations combined with contribution index analysis). Our focus on quantifying uncertainty contributions from individual uncertainty elements allows us to rank the contributions to uncertainty across sub-sectors.

A significant challenge for both our analysis of uncertainty and for the main carbon stock change calculations undertaken by the NGHGI is the availability of species- and region-specific input to the carbon models. Many of the data used to derive the necessary parameter values are from research published many decades ago. In such cases, the underlying datasets used to inform the published summary statistics are no longer available, making it difficult to estimate an error bar for the modeling parameters. The results of our sensitivity analysis show that the magnitude of the error bar applied to the modeling parameters can significantly affect the uncertainty estimation and alter the relative importance of various parameters with respect to uncertainty contributions.

Furthermore, many of the modeling parameters used in the estimation of tree carbon are species specific; however, when data is not available for a given species or region, data for a similar species or species group is assigned (e.g., Miles and Smith 2009). For other parameters, data are presented for broad species groups (e.g., component ratio coefficients are given only for hardwood and softwood categories).

In our Monte Carlo framework, it is possible that the number of parameters that are allowed to vary within a parameter group has an impact on the estimated modeling uncertainty contributed by that group and therefore might have an impact on the ranking among the parameter groups. For example, we find that the volume coefficients contribute the largest uncertainty among the nine sets of parameter groups that we analyze. For the eastern Texas dataset that we analyze, there are 81 different species-specific sets of volume coefficients applied in the calculation. For nearly all trees in this dataset, a "set" of volume coefficients includes two coefficients with bole-wood gross cubic-foot volume calculated according to the equation: volume = coefficient1 + [coefficient2 x diameter^2 x height]. Any tree in the dataset that is assigned the same mean values for the set of coefficients is likewise assigned the same 10,000 iterates of the two coefficients. On one hand, this aspect of the framework might limit the overall variation contributed by this parameter since all "alike" trees are assigned the same 10,000 iterates for the volume coefficients. On the other hand, the fact that there are 81 different sets of coefficients that are allowed to vary in the calculation might increase the overall variation attributed by this parameter group in relation to other parameter groups where there are fewer sets of coefficients/parameters that are allowed to vary. This is not necessarily a confounding artifact of the calculation, though, because even if the variance is larger because more parameters are allowed to vary, this is a valid reason to focus efforts on refinement of one parameter group rather than another. Finally, stratification of the land base is used as a variance reduction technique (Bechtold and Patterson 2005). The use of a different stratification framework (e.g., larger number of canopy cover bins) can result in a different magnitude of sampling error than what is calculated for eastern Texas using the NLCD stratification.

2.2 Carbon stock change in forest litter

NGHGI METHODS

Litter is a pool of carbon comprised of duff, humus, and fine woody debris that is found on the forest floor above the soil. The NGHGI defines litter to include woody fragments with diameters up to 7.5cm (NGHGI 2018). The NGHGI uses plot-level estimates of litter carbon, collected through the Forest Inventory and Analysis (FIA) program, and then scales plot estimates to total U.S. forest area to estimate annual litter carbon stocks. Annual litter CO_2 flux is calculated as the litter carbon stock change between year *t* and *t-1*. FIA has litter measurements for 1/16 of FIA plots starting in 2011 (Domke et al. 2016). At each sample point, multiple litter thickness measurements are taken, and the litter layer within sampling frames are removed for lab analysis to determine carbon content (Domke et al. 2016). Since 96% of FIA plots do not have litter samples, Domke et al. (2016) developed a machine learning model to predict litter carbon stocks on un-sampled plots, using predictive variables like latitude, longitude, elevation, forest type, stand age, site index, aboveground live tree carbon, and others. The model was iteratively trained on 70% of the FIA litter plot data, and tested on the remaining 30%. Model predictions were combined with a randomly generated variable to represent sample error. Plot estimates are then scaled by area weights to cover total forest area, similar to other forest carbon pools.

PROJECT METHODS

We estimate the 95% confidence interval for litter carbon stock change that accounts for modeling error. We are not able to replicate the method described by Domke et al. (2016) because their data is not yet available in FIA and recreating the Random Forests machine learning model described above was outside the scope of our project. Instead, we use a simplified method using summary data from Domke et al. (2016). A significant shortcoming of our approach is that it requires assuming the covariance of litter carbon stocks between two time periods, which means that we are setting the variance of the CO_2 flux by assumption. Additional reporting of uncertainty by carbon pool in the NGHGI would be useful to avoid the need for this assumption.

Similar to other forest carbon pools, our estimate is informed by FIA data for eastern Texas. We describe the FIA program and database (USDA Forest Service 2018) in detail in Section 2.1 above. For the litter carbon analysis, we use the FIA data only to identify the distribution of forest-type groups in eastern Texas; thus, our estimates of national litter carbon stock change might be biased by our focus on eastern Texas since the national forest-type distribution is not identical to that in Texas. We focus our analysis on forest land remaining forest land (FRF) area.

For the FRF analysis, we select all eastern Texas Phase 2 ground plots in the subplot–condition change matrix (SUBP_COND_CHNG_MTRX table of the FIA Database) that correspond to EVALID 481723 and have at least one geographic area that is FRF over the re-measurement interval (that is, the geographic area has COND_STATUS_CD=1, indicating accessible forest land, in both the previous and current measurement periods). Of the 3,778 eastern Texas FIA ground plots having EVALID 481723, 2,242 plots have at least one geographic area that is FRF. For each of these plots, we identify the forest type for the previous measurement period using the FORTYPCD attribute in the condition (COND) table. FIA aggregates the individual forest types defined by FORTYPCD into supergroups (Appendix D of Burrill et al. 2017). For example, the willow forest type (FORTYPCD=704) is assigned to the elm–ash–cottonwood supergroup (code 700). In the FRF dataset for eastern Texas, 37 individual forest types (FORTYPCD values) are represented in the previous measurement period, corresponding to 11 FIA forest-type supergroups: longleaf–slash pine, loblolly–shortleaf pine, other eastern softwoods, oak–pine, oak–hickory, oak–gum–cypress, elm–ash–cottonwood, other hardwoods, woodland hardwoods, exotic hardwoods, and non-stocked.

Smith et al. (2003) aggregate the forest-type groups available in the FIA Database into a smaller set of forest types. For the south central region of the United States, which includes Texas, Smith et al. (2003) assign seven forest-type groups (their Table 1). We further aggregate the Smith et al. (2003) forest-type groups to achieve the four forest-type groups for the southern United States for which Domke et al. (2016) report summary statistics for litter carbon stocks (their Table 1): non-stocked, hardwood, pine, and mixed conifer. The classification key that we use is shown below in Table T-4. Forest types corresponding to the FIA supergroups woodland hardwoods, exotic hardwoods, and other hardwoods exist in the eastern Texas dataset but are not explicitly listed in Table 1 of Smith et al. (2003) for the south central region of the United States. We assign these forest types to the over-arching hardwood group. The eastern redcedar forest type (FORTYPCD=171, belonging to FIA supergroup "other eastern softwoods") could conceivably be assigned to either the pine or mixed conifer groups of the Domke et al. (2016) classification. Because this dataset lacks any other forest types that fall into the mixed conifer group, we assign the eastern redcedar to the mixed conifer group, thereby providing increased diversity in the forest type distribution. For the northeast, northern prairie states, south central, and southeast regions of the United States, Smith et al. (2003) define an oak–pine forest type that is composed solely of the oak–pine FIA supergroup; however, for the northern lake states, Smith et al. (2003) define a pine forest type by combining the oak–pine FIA supergroup with all other pine groups. We follow this guidance and assign oak–pine to the overarching pine group.

For the previous measurement period for each plot, considering only the FRF parts of the plot, the fraction of the plot area that belongs to each of the four aggregated forest-type groups is calculated using the subplot type proportion change (SUBPTYP_PROP_CHNG) attribute from the SUBP_COND_CHNG_MTRX table. Considering the entire FRF portion of the plot, the predominant forest type (i.e., the forest type accounting for the largest fraction of plot area) is assigned as the plot-level forest type for the previous measurement period. In a limited number of cases (9 plots in the previous measurement period), multiple forest types account for identical fractions of the plot area. In such cases, we institute the preferred order of assignment: pine > hardwood > mixed conifer > non-stocked. That is, we preferentially assign the plot as stocked forest rather than non-stocked forest; among the stocked forest types, we preferentially assign the forest type with the smallest standard deviation for litter carbon stock as given by Domke et al. (2016).

To estimate the model-based error associated with the annual change in litter carbon stock for FRF, we apply Monte Carlo iterations to the set of FRF plots in eastern Texas. For each plot, we generate distributions of litter carbon stock for both the previous period and the next period (previous period plus one year), applying the same forest type for each of the two time points. We assume that the plot-level carbon stocks in the two periods are jointly distributed with positive covariance and assume carbon stocks are normally distributed. To generate the distribution for the previous period, we apply the mean carbon stock by forest type given by Table 1 of Domke et al. (2016) for the southern United States: 18.96 metric tons CO_2 ha^{-1} for non-stocked forest; 27.43 metric tons CO_2 ha^{-1} for pine forest; 28.82 metric tons CO_2 ha^{-1} for hardwood forest; and 57.02 metric tons CO_2 ha^{-1} for mixed conifer forest.

For each plot, we apply the same predominant forest type in the next period (previous period plus one year) that we apply in the previous period. The next period litter carbon stock distribution is derived by applying the mean value from Domke et al. (2016) for the given forest type, but the mean value in the next period is increased by 0.06 metric tons CO_2 ha^{-1}, so that the sequestration rate for the plot between the previous and next periods will be identical to the national average litter carbon sequestration rate of 0.06 metric tons CO_2 ha^{-1} y^{-1}. We estimated the national average annual carbon flux per ha (sequestration of 0.06 metric tons CO_2 ha^{-1} y^{-1}) from forest litter for FRF by dividing the total national carbon sequestration for 2016 for FRF litter (16.1 MMT CO_2 y^{-1}; Table 6.10 of NGHGI 2018) by the total national FRF area in 2016 (272,260,000 ha; Table 6.12 of NGHGI 2018). The total FRF area figure accounts for managed forest land in the conterminous United States and southeastern and south central coastal Alaska.

For each forest type, we assign the variance of the litter carbon stock as the modeling mean-squared error for litter carbon reported by the NGHGI (Annex 3, sub-section 3.13): 1050 [metric tons CO_2 ha^{-1}]^2.

We apply a very high level of covariance between the litter carbon stocks in the two periods; that is, we assume a covariance that is 0.999 times the magnitude of the variance. Note that by choosing the covariance between stocks over time we are choosing the variance of litter CO_2 flux – a shortcoming of our method and a reason why reporting carbon pool-level uncertainties in the NGHGI would be useful.

We used the R programming language (R Core Team 2018) for analysis and made use of the "rmvnorm" function from the "mvtnorm" package (Genz et al. 2019). We generated 10,000 pairs of litter carbon stock for the previous and next periods for each plot. Element-by-element subtraction (next period carbon stock minus previous period carbon stock) results in a plot-level distribution of annual carbon flux (metric tons CO_2 ha^{-1} y^{-1}). With this formulation, positive values indicate carbon sequestration.

We apply equations 1–3 from Ogle et al. (2010) to estimate the regional annual litter carbon stock change (i.e., the litter carbon stock change for all of eastern Texas) and the associated modeling error. First, the regional litter carbon stock change for any individual Monte Carlo iterate (units: metric tons CO_2 y^{-1}) was calculated by multiplying, for each plot, the plot-level stock change for that iterate (units: metric tons CO_2 ha^{-1} y^{-1}) by that plot's area weight (units: ha) and then summing this product over all plots (equation 1 of Ogle et al. 2010). This process was repeated for each of the 10,000 Monte Carlo iterates. As described in Section 2.1, each plot in eastern Texas is assigned to one of nine estimation unit–stratum combinations (here, simply referred to as "stratum"). For this analysis, each plot in a given stratum is assigned the same area weight. The area weight for each plot indicates the total area (ha) of eastern Texas FRF land represented by the plot. The area weights for the plots in each stratum were calculated by dividing the area (ha) of FRF land in that stratum by the number of FRF-containing plots in that stratum. Secondly, the mean annual litter carbon stock change for eastern Texas was calculated by taking the average of the 10,000 regional stock change iterates (equation 2 of Ogle et al. 2010). We assume that the derived annual flux is representative of the contemporary era and therefore take this flux as an estimate for 2016. Finally, the model-based variance (equation 3 of Ogle et al. 2010) was calculated using the outputs of equations 1 and 2. In this analysis, the annual sequestration rate for every plot is forced to the national-mean sequestration rate; therefore, we are unable to calculate a sampling error associated with litter carbon flux.

We derive the 95% confidence interval from the distribution of 10,000 iterates. This process provides the 95% confidence interval for annual litter carbon stock change for FRF in eastern Texas. To estimate the 95% confidence interval for litter carbon stock change for FRF in the entire United States, we apply the percentage errors for eastern Texas to the mean U.S. litter carbon stock change for 2016 from NGHGI (2018). The total contribution to uncertainty is calculated as the range of the 95% confidence interval for the United States (upper bound minus lower bound).

Table T-4: Classification key used to assign forest types from the FIA Database to those used by Domke et al. (2016) for litter carbon stocks

Forest type from FIA Database	Forest type from Smith et al. (2003)	Forest type for our litter analysis
Oak–Gum–Cypress	Bottomland hardwood [a]	Hardwood
Elm–Ash–Cottonwood		
Oak–Hickory	Upland hardwood [a]	
Woodland hardwoods	Not indicated	
Exotic hardwoods	Not indicated	
Other hardwoods	Not indicated	
Longleaf–Slash Pine	Pine [b]	Pine
Loblolly–Shortleaf Pine		
Oak–Pine	Oak–Pine	
Other eastern softwoods	Not indicated	Mixed conifer
Nonstocked	Nonstocks	Nonstocked

a) Smith et al. (2003) additionally assign the FIA group Maple–Beech–Birch to upland hardwoods and the FIA group Aspen–Birch to bottomland hardwoods. The eastern Texas dataset has neither of these FIA groups.
b) Smith et al. (2003) divide the pine group into naturally occurring pine and planted pine groups, but we combine these into a single group here.

RESULTS

We estimate a mean litter carbon sequestration for eastern Texas FRF land of 0.29 MMT CO_2 (over 1-year time step) based on the Monte Carlo analysis using 10,000 iterations. This is the expected stock change considering that (1) we force the sequestration rate to the national mean (0.06 metric tons CO_2 ha^{-1} y^{-1}) and (2) the area of FRF in eastern Texas for this analysis is 4.75 Mha. The estimated model-based variance is 0.022 [MMT CO_2]^2. The estimated 95% confidence interval for eastern Texas litter carbon stock change is -0.58 MMT CO_2 to 0.01 MMT CO_2, where positive values indicate emission and negative values indicate sequestration. The estimated percentage errors are -103.9% (lower bound) and 102.1% (upper bound). Applying these percentage errors to the mean litter carbon stock change for the United States for 2016 (-16.1 MMT CO_2; NGHGI 2018) results in a 95% confidence interval of -32.8 MMT CO_2 (a sequestration) to 0.3 MMT CO_2 (an emission). The contribution to uncertainty is 33.2 MMT CO_2.

DISCUSSION

The Domke et al. (2016) litter carbon analysis points to multiple sources of uncertainty in estimating litter carbon stocks, including first modeling litter carbon at all FIA plots using machine learning methods and extrapolating FIA plot values to total U.S. forest area. Due to the complexity of the Random Forests machine learning model and lack of data, we were not able to replicate litter carbon stock estimation methods, and were not able to further attribute litter carbon uncertainty across model and sampling error.

We tested the stability of our results to the number of Monte Carlo iterations, finding nearly identical 95% confidence intervals for the United States using 50,000 iterations (-32.7 MMT CO_2 to 0.4 MMT CO_2) as we found with 10,000 iterations (-32.8 MMT CO_2 to 0.3 MMT CO_2). We additionally tested the sensitivity of our results to the prescribed level of covariance between the carbon stocks in the two time periods (using 10,000 iterations for each analysis). The results of our sensitivity analysis are shown in

Table T-5. This shows that results are highly sensitive to our assumption of litter carbon stock covariance across time periods. For this reason, we don't include litter carbon in the top 10 sources of NGHGI uncertainty in the Executive Summary, though it is possible both litter and soil carbon (as we discuss further below) should be considered high priorities.

Table T-5: Sensitivity of litter carbon uncertainty results to covariance assumption

Covariance (as a fraction of variance)	Percentage error	Eastern Texas		United States		
		Lower bound ($MMT\ CO_2$)	Upper bound ($MMT\ CO_2$)	Lower bound ($MMT\ CO_2$)	Upper bound ($MMT\ CO_2$)	Uncertainty contribution ($MMT\ CO_2$)
0.5	-2,298%, 2,258%	-6.9	6.2	-386.1	347.4	733.5
0.75	-1,631%, 1,602%	-5.0	4.3	-278.6	241.8	520.5
0.9	-1,034%, 1,016%	-3.3	2.6	-182.6	147.5	330.2
0.95	-732.6%, 719.8%	-2.4	1.8	-134.0	99.8	233.8
0.999	-103.9%, 102.1%	-0.6	0.01	-32.8	0.3	33.2
0.9999	-32.9%, 32.3%	-0.4	-0.2	-21.4	-10.9	10.5

2.3 Carbon stock change in forest soils

NGHGI METHODS

The annual net CO_2 flux from the forest soil carbon pool is calculated as the change in soil carbon stock between year *t* and year *t-1*. The method used to estimate soil carbon stocks on U.S. forest land is described by Domke et al. (2017); we provide only a brief outline here. Soil cores to a depth of 20 cm are taken on 1/16 of forested FIA ground plots, followed by lab analysis to estimate soil carbon stock. The NGHGI combines the FIA soil carbon dataset with forest soil carbon measurements taken by the International Soil Carbon Monitoring Network (ISCN) to develop a model that allows estimation of soil carbon stocks on the measured FIA plots to a depth of 100 cm. A Random Forests machine learning model is then combined with this refined set of FIA soil estimates down to 100 cm to predict forest soil carbon stocks on all forested FIA plots based on measured variables, including: latitude, longitude, elevation, forest-type group, precipitation, temperature, evapotranspiration, soil order, and surface geology. The standard extrapolation to total forest area is then applied to calculate total U.S. soil carbon stocks.

PROJECT METHODS

We estimate the 95% confidence interval for soil carbon stock change that accounts for modeling error using a method that is similar to that applied for litter carbon stock change (Section 2.2). We apply this simplified method based on summary statistics for soil carbon stocks from Domke et al. (2017) since the method used in the NGHGI (2018) is beyond the scope of this analysis. We repeat here the same caveat that we made for the litter carbon pool: A significant shortcoming of our approach is that it requires assuming covariance of soil carbon stocks between two time periods, which means that we are setting the variance of the CO_2 flux by assumption. While the NGHGI reports variance in the soil carbon stock, it does not report uncertainty for soil carbon stock change; reporting this latter statistic would allow us to better compare the uncertainty for soil carbon fluxes with the uncertainties for other forest ecosystem carbon pools.

For our analysis, we again make use of the eastern Texas Phase 2 ground plots from the FIA Database (USDA Forest Service 2018). We use the FIA data only to identify the locations of plots in eastern Texas with FRF area. We identify the rows of SUBP_COND_CHNG_MTRX table that correspond to plots associated with EVALID 481723 that have any accessible forest land in either the previous or current measurement period. On this subset of plots, we compare the sizes of the forest-containing land use regimes and then select those for which the FRF category is largest among these. We identify the latitude and longitude coordinates for each of these 2,193 plots using the PLOT table of the FIA Database. Based on these coordinates, we identify the dominant soil order for each plot, using a dataset derived from the SSURGO database (Soil Survey Staff 2019) that was prepared for us by Steve Campbell at the USDA Natural Resources Conservation Service in Portland, OR. Our dataset of 2,193 plots encompasses 6 different soil orders: (1) Alfisols (1,024 plots); (2) Entisols (108 plots); (3) Inceptisols (156 plots); (4) Mollisols (25 plots); (5) Ultisols (704 plots); and (6) Vertisols (159 plots). In a limited number of cases (17 plots), no soil order could be assigned. For the analysis of soil carbon, we use the FIA data only to identify the distribution of soil orders in eastern Texas; thus, our estimates of soil carbon stock change might be biased by our focus on eastern Texas since the national soil order distribution is not identical to that in Texas.

We use Monte Carlo iterations to estimate modeling error for the annual change in soil carbon stock. For each plot, we generate distributions of soil carbon stock for both the previous period and the next period (previous period plus one year), using the same soil order for both time points. We assume that the plot-level carbon stocks in the two periods are jointly distributed with positive covariance and assume lognormal distributions for the carbon stocks. Soil carbon stock means, measured to 100cm, by soil type along with minimum and maximum values, were taken from Domke et al. (2017), their table 3. First we constructed a triangular distribution for each soil type using the reported mean, minimum, and maximum values, then augmented the minimum and maximum for each soil type by the additional standard deviation from using Random Forests to extrapolate soil carbon measurements to all FIA plots. This augmented triangular distribution was then used to parameterize a lognormal distribution for each soil type, to allow for use of covariance across time steps. We applied the statistics for the "all soils" category to the 17 plots for which a soil order was not assigned.

We force the annual sequestration rate for each plot to be identical to the national average sequestration rate of 0.50 metric tons CO_2 ha^{-1} y^{-1}, which we estimated by dividing the total national soil carbon sequestration for 2016 for FRF (135.3 MMT CO_2 y^{-1} for mineral plus organic soils, excluding drained organic soils; Table 6.10 of NGHGI 2018) by the total national FRF area in 2016 (272,260,000 ha; Table 6.12 of NGHGI 2018). The total FRF area figure accounts for managed forest land in the conterminous United States and southeastern and south central coastal Alaska. We apply a very high level of covariance between the soil carbon stocks in the two periods; that is, we assume a covariance that is 0.999 times the magnitude of the variance.

We used the R programming language (R Core Team 2018) for analysis and made use of the "rlnorm.rplus" function from the "compositions" package (van den Boogaart 2018). We generated 50,000 pairs of soil carbon stocks for each period for each plot. Element-by-element subtraction (next period carbon stock minus previous period carbon stock) results in a plot-level distribution of annual carbon flux (metric tons CO_2 ha^{-1} y^{-1}). We apply equations 1–3 from Ogle et al. (2010) to estimate the regional annual soil carbon stock change (i.e., the soil carbon stock change for all of eastern Texas) and the associated modeling error. We describe these equations in detail in Section 2.2 above. Because the annual sequestration rate for every plot is forced to the national mean sequestration rate in our analytical framework, we are unable to calculate a sampling error for soil carbon flux. We derive the 95% confidence intervals for soil carbon stock change for both eastern Texas and the entire United States using the same method as described in Section 2.2 for litter carbon.

RESULTS

We estimate a mean soil carbon sequestration for eastern Texas FRF land of 2.4 MMT CO_2 over a 1-year time step. Using a Monte Carlo analysis that prescribes the covariance between carbon stocks in the two periods as 0.999 times the magnitude of the variance, the estimated model-based variance for eastern Texas is 1.35 $[\text{MMT } CO_2]^2$. The estimated 95% confidence interval for eastern Texas soil carbon stock change is -4.7 MMT CO_2 to -0.1 MMT CO_2, where negative values indicate sequestration. The percentage errors are -94.4% (lower bound) and 94.6% (upper bound). Applying these percentage errors to the mean soil carbon stock change for the United States for 2016 (-135.3 MMT CO_2; NGHGI 2018) results in a 95% confidence interval of -263.1 MMT CO_2 to -7.4 MMT CO_2. The contribution to uncertainty is 255.7 MMT CO_2.

DISCUSSION

Similar to litter carbon, we were not able to attribute soil carbon uncertainty across model and sampling error due to the complexity of the Random Forests machine learning model.

We tested the sensitivity of our results to the prescribed level of covariance between the carbon stocks in the two time periods (using 50,000 iterations for each analysis). The results of our sensitivity analysis are shown in Table T-6. This shows that results are highly sensitive to our assumption of soil carbon stock covariance across time periods. For this reason, we don't include soil carbon in the top 10 sources of NGHGI uncertainty in the Executive Summary, though it is possible both litter and soil carbon should be considered high priorities. Even assuming the highest amount of covariance between time periods (0.9999), the uncertainty contribution from soils is 81.2 MMT CO_2, on par with the contribution from tree volume coefficients which are the second largest source of uncertainty in the LULUCF GHG inventory.

Table T-6: Sensitivity of soil carbon uncertainty to covariance assumption

Covariance (as a fraction of variance)	Percentage errors (lower bound, upper bound)	Eastern Texas		United States		
		Lower bound (MMT CO_2)	Upper bound (MMT CO_2)	Lower bound (MMT CO_2)	Upper bound (MMT CO_2)	Uncertainty contribution (MMT CO_2)
0.5	-1,936%, 1,948%	-51.7	46.9	-2,754.4	2,500.7	5,255.2
0.75	-1,406%, 1,1415%	-37.9	33.0	-2,038.3	1,778.8	3,817.1
0.9	915%, 913%	-25.2	20.1	-1,373.5	1,099.9	2,473.4
0.95	-655%, 653%	-18.6	13.6	-1,021.7	748.4	1,770.1
0.999	-94.4%, 94.6%	-4.7	-0.1	-263.1	-7.4	255.7
0.9999	-30.0%, +30.0	-3.1	-1.7	-175.9	-94.7	81.2

2.4 Non-CO_2 from forest fires

NGHGI METHODS

The NGHGI quantifies CH_4 and N_2O emissions from forest fires in the conterminous United States (CONUS) and Alaska following IPCC methodology (IPCC 2006). Equation 3 provides the basic structure of the emissions calculation (IPCC 2006).

Equation 3: Non-CO_2 emissions from forest fires (NGHGI 2018)

$$Emissions = Burned\ area \times Fuel\ available \times Combustion\ factor \times Emission\ factor$$

This section describes the approach used the 2018 NGHGI to develop the input parameters for this equation; updates from the 2019 NGHGI are described in the "Discussion" section below.

Annual estimates of burned area are based on a combination of input data from multiple sources. The Monitoring Trends in Burn Severity (MTBS) dataset provides annual fire data (e.g., location, intensity, and burned area), but does not delineate the fires by ecosystem type (MTBS Data Summaries 2015). A forest area dataset approximately representative of 2002 from Ruefenacht et al. (2008) is used to determine the fraction of the MTBS burned area that occurs on forest land. Alaskan forests are additionally subset into managed and unmanaged areas based on Ogle et al. (2018). All fires in Alaska are assumed to occur in boreal forest.

For the conterminous United States, state-level fuel availabilities (mass of dry matter available per unit area) are derived using FIA plot data (USDA Forest Service 2015). For each measurement plot in a state, the fuel available for wildfires is calculated as the plot-level biomass density, accounting for litter, downed dead wood, understory vegetation, and aboveground biomass in living and standing dead trees. Similarly, the fuel available for prescribed fires is calculated as the plot-level biomass density, accounting for litter, downed dead wood, and aboveground biomass in standing dead trees. The NGHGI reports that, for a given state, the plot-level fuel availabilities are generally lognormally distributed.

The combustion factor (mass of dry matter burned per mass of dry matter available) applied for the conterminous United States is the default factor for temperate forests from IPCC (2006). A combined parameter that takes into account both fuel availability and the combustion factor for boreal forests from IPCC (2006) is applied for all fires in Alaska. The emission factors for CH_4 and N_2O (mass of gas emitted per mass of dry matter burned) are likewise from IPCC (2006). Emissions of CH_4 and N_2O are converted to CO_2 equivalents using 100-year global warming potentials (GWPs) from IPCC (2007). The NGHGI calculates non-CO_2 emissions from forest fires separately by state, year, and fire type (wildfires and prescribed fires).

The NGHGI quantifies the 95% confidence intervals for non-CO_2 emissions from forest fires using Monte Carlo iterations. The variable parameters include: (1) burned area (normally distributed with standard deviation that is 4% of the mean), sampled by year; (2) state-level fuel availability for conterminous United States (lognormally distributed for each fire type), sampled by state and year; (3) combustion factor for conterminous United States (normally distributed, truncated at zero), sampled by year; (4) combined fuel availability–combustion factor for Alaska (normally distributed, truncated at zero), sampled by year; and (5) emission factors (normally distributed, truncated at zero), sampled by year. The lognormal distributions of state-level fuel availabilities are derived from fitting the FIA plot data. For factors 3–5, both the means and standard deviations are those reported by IPCC (2006). No uncertainty is assigned to the GWPs.

PROJECT METHODS

We use Monte Carlo iterations (n=1,000,000) to separately quantify the 95% confidence intervals for CH_4 and N_2O emissions from forest fires. We apply the same underlying computational framework as is applied in the NGHGI (2018), but additionally quantify the percent contribution to uncertainty from several uncertain parameters. The Monte Carlo analysis was performed using the R programming language (R Core Team 2018) and made use of the "truncnorm" package (Mersmann et al. 2018). The input parameters for the Monte Carlo analysis are summarized in Table T-7. We focus our calculation on year 2014 since this is the most recent year for which burned area estimates were made available to us. We apply the same percentage uncertainty for the burned area as is suggested by the NGHGI (i.e., standard deviation is 4% of the mean). Because the NGHGI does not report state-level burned area and fuel availabilities for the conterminous United States, we quantify emissions using total burned area and the mean fuel availability for the conterminous United States.

We follow the contribution index analysis shown in Equation 1 above, with 1,000,000 Monte Carlo iterations for each element of uncertainty. For non-CO_2 emissions from forest fires, we quantify the relative contribution to uncertainty from five parameter groups: (1) burned area; (2) fuel availability for the conterminous United States; (3) combustion factor for the conterminous United States; (4) combined fuel availability–combustion factor for Alaska; and (5) emission factor. We assume independence for all parameters.

Table T-7: Input parameters for contribution index analysis of non-CO_2 emissions from forest fires

Parameter	Mean	Standard deviation	Probability distribution
CONUS total wildfire burned area	679,000 ha [a]	27,160 ha [b]	Normal
CONUS total prescribed fire burned area	10,650 ha [c]	426 ha [b]	Normal
Alaska total burned area	346,850 ha [d]	13,874 ha [b]	Normal
CONUS wildfire fuel availability	149 metric tons dry matter available ha^{-1} [e]	159 metric tons dry matter available ha^{-1} [f]	Lognormal
CONUS prescribed fire fuel availability	36 metric tons dry matter available ha^{-1} [e]	24 metric tons dry matter available ha^{-1} [f]	Lognormal
CONUS combustion factor	0.45 [g]	0.16 [g]	Normal, truncated at zero
Alaska combined fuel availability–combustion factor	41.0 metric tons dry matter consumed ha^{-1} [g]	36.5 [g]	Normal, truncated at zero
CH_4 emission factor	4.7 g CH_4 emitted kg^{-1} [dry matter burned] [g]	1.9 [g]	Normal, truncated at zero
N_2O emission factor	0.26 g N_2O emitted kg^{-1} [dry matter burned] [g]	0.07 [g]	Normal, truncated at zero

a) Estimate reported by NGHGI (2018), based on data from MTBS Data Summaries (2015) and Ruefenacht et al. (2008).
b) Calculated as 4% of the mean, following NGHGI.
c) Calculated from data reported by NGHGI (2018) and supplemental materials provided by NGHGI Team. Burned area estimates from NGHGI are based on MTBS Data Summaries (2015) and Ruefenacht et al. (2008).
d) Estimate reported in supplemental materials provided by NGHGI Team. Burned area estimates for Alaska are based on Ogle et al. (2018), MTBS Data Summaries (2015), and Ruefenacht et al. (2008).

e) Estimates reported in supplemental materials provided by NGHGI Team. Based on FIA plot data (USDA Forest Service 2015).
f) Derived from 5th and 95th percentiles reported in supplemental materials provided by NGHGI Team. Based on FIA plot data (USDA Forest Service 2015).
g) IPCC (2006).

RESULTS

The 2014 estimates and 95% confidence intervals for CH_4 and N_2O emissions from forest fires are shown in Table T-8. The estimates for 2014 (7.2 MMT CO_2e from CH_4 and 4.7 MMT CO_2e from N_2O) are identical to those reported in the NGHGI (2018) despite the fact that we applied CONUS-mean fuel availabilities and CONUS-total burned area estimates instead of state-level values. There is significant interannual variability associated with non-CO_2 emissions from forest fires (see Table 6-16 of NGHGI 2018). The emissions estimates for 2016, the only year for which uncertainties are reported in the NGHGI, are more than 2.5 times larger than those for 2014. We estimate larger relative uncertainties for 2014 emissions (about +250%) than the NGHGI estimates for 2016 emissions (about +120%). However, the magnitude of the 95% confidence interval, taken as the difference between the 97.5th percentile and the 2.5th percentile, respectively, is similar for our 2014 estimate and the 2016 estimate from the NGHGI: 25.3 MMT CO_2e for CH_4 (our 2014 estimate) vs. 29.9 MMT CO_2e (NGHGI 2016 estimate) and 15.5 MMT CO_2e for N_2O (our 2014 estimate) vs. 22.3 MMT CO_2e (NGHGI 2016 estimate).

Table T-8: Uncertainty estimates for non-CO2 emissions from forest fires

Gas	2014 estimate (MMT CO_2e)	Lower bound [a] (MMT CO_2e)	Upper bound [a] (MMT CO_2e)	Lower bound [b] (%)	Upper bound [b] (%)
CH_4	7.2	0.8	26.1	-89%	263%
N_2O	4.7	0.8	16.3	-83%	247%
Total	**11.9**	**2.0**	**41.0**	**-83%**	**245%**

(a) Lower and upper bounds correspond to 2.5th and 97.5th percentiles (95% confidence interval).
(b) The relative uncertainties are calculated as a percentage of the 2014 estimate.

The results of the contribution index analysis, which is based on total non-CO_2 emissions from forest fires, are shown in T-9. Among the five uncertain parameter groups, the fuel availabilities applied to wildfires and prescribed fires in the conterminous United States together contribute the largest fraction (74%) of total uncertainty associated with non-CO_2 emissions from forest fires. The combustion factor for the conterminous United States contributes a similar amount of uncertainty (9%) as is contributed by the emission factors (16%). Negligible uncertainty is contributed by uncertainty in burned area estimates (0.5%) and uncertainty in the combined fuel availability and combustion factor applied to fires in Alaska (0.8%).

Table T-9: RESULTS - Contributions to uncertainty for non-CO_2 emissions from forest fires

Variable held constant	Range of 95% confidence interval (MMT CO_2e)	Contribution to uncertainty (%)	Contribution to uncertainty (MMT CO_2e)
None (all vary)	39.0	–	–
Burned area	38.8	0.8	0.3
CONUS fuel availabilities	19.5	73.6	28.7
CONUS combustion factor	36.5	9.4	3.7
Alaska fuel availability – combustion factor	38.8	0.8	0.3
Emission factors	34.9	15.5	6.0

DISCUSSION

The newest iteration of the NGHGI (2019), which covers 1990–2017, introduces a number of updates to the input parameters for this GHG flux calculation: (1) delineation of forest within burned areas is now based on the National Land Cover Dataset (Homer et al. 2015) rather than Ruefenacht et al. (2008); (2) fuel availabilities derived from FIA plot data are now aggregated by ecological regions rather than by state; and (3) variable combustion factors based on burn severity, as specified by the MTBS dataset, are now applied instead of application of a single combustion factor for all fires in the conterminous United States. The updates to the input parameters resulted in a small downward revision in the emissions estimates for 2014: 6.1 MMT CO_2e for CH_4 and 4.0 MMT CO_2e for N_2O, for a total of 10.1 MMT CO_2e (compared to 11.9 MMT CO_2e reported by the previous NGHGI).

Our analysis suggests that the fuel availabilities for the conterminous United States make the largest contribution to uncertainty. Because we apply national-mean fuel availabilities, rather than state-level fuel availabilities, to all fires in the conterminous United States, we might overestimate both the overall uncertainty and the uncertainty attributed to this parameter. Grouping of fuel availabilities by ecological region instead of by state, as is done in the newest iteration of the NGHGI, might reduce the error bars on the fuel inputs, thereby resulting in an overall reduction in the total uncertainty from non-CO_2 emissions from forest fires.

2.5 Carbon stock change in harvested wood products

NGHGI METHODS

Changes in carbon stock stored in harvested wood products (HWP) in use and HWPs in waste disposal sites are both accounted for in the NGHGI. This is necessary because not all harvested wood from forests is immediately released to the atmosphere – long-lived wood products can store a significant percentage of harvested carbon for decades. Thus, carbon removed from forest biomass due to harvest must be allocated across CO_2 emissions that immediately enter the atmosphere, carbon that enters a variety of wood products (e.g. timber, paper) for some period of storage, and CO_2 that enters the atmosphere through decay of wood products. HWP calculations are estimated in the NGHGI through Tier 2 and 3 methods, using U.S.-specific data and models.

The NGHGI utilizes the methods outlined in Skog (2008) to estimate changes in carbon stored in wood products, both those in use and those in waste disposal sites. Skog's methods are consistent with the

IPCC (2006) "production method," which accounts for all wood grown and harvested within the United States stored in products. That is, imported wood products are ignored and exports are accounted for. The NGHGI accounts for carbon from wood products harvested in 1900 through the present, accounting for gains in stored carbon from new harvest and production as well as losses of carbon from disposal and decay.

Key equations used to estimate carbon in HWPs can be found in Skog (2008): equations 1–5 for wood products in use and equations 6–10 for disposed and decaying wood products. The equations themselves are long but relatively intuitive so we do not reproduce them here.

Key parameters and inputs for estimating annual carbon stored in wood products in use are:

- Discard rate of wood product for end use *j* (paper product, single-family housing, multifamily housing, residential upkeep and improvement, other)
- Fraction of primary product *i* (plywood, lumber, pulpwood, roundwood, etc.) going to end use *j*
- Amount of carbon in solid wood or paper products
- Amount of sawlogs harvested annually
- Amount of sawlogs imported annually
- Amount of sawlogs exported annually
- Fraction of total fiber used to make paper/paperboard from non-wood fiber
- Fraction of imported woodpulp to make paper/paperboard
- Total pulpwood used to make paper/paperboard annually
- Amount of pulpwood imported annually
- Amount of pulpwood exported annually
- Amount of carbon in recovered, exported fiber pulp
- Amount of carbon in recovered, exported paper
- Amount of carbon in exported woodpulp[1]

Key parameters and inputs for estimating annual carbon stored in wood products in waste disposal sites are:

- Amount of carbon discarded from solid wood products annually
- Amount of carbon discarded from paper products annually
- Fraction of discarded solid wood products sent to dumps and landfills
- Fraction of discarded paper products sent to dumps and landfills
- Fraction of discarded paper and solid wood products sent to dumps rather than landfills annually
- Fraction of discarded paper and solid wood products burned annually
- Fraction of discarded paper and solid wood products recovered for recycling or export annually
- Fraction of discarded paper and solid wood products composted annually
- Fraction of carbon in solid wood products in landfills that is degradable
- Fraction of carbon in paper in landfills that is degradable
- Half-life of degradable carbon in paper and solid wood products in dumps or landfills

Skog (2008) provides sources of information for all these pieces of data and parameter estimation.

[1] Pulpwood is wood grown purposefully for paper production. Woodpulp is an intermediate material derived from pulpwood used to produce paper. Both pulpwood and woodpulp can be imported or exported and need to be accounted for separately.

PROJECT METHODS

We directly use results from Skog et al. (2004), which utilizes the contribution index approach to evaluate contributions to uncertainty when calculating carbon stock changes in harvested wood products. Skog et al. (2004) evaluates uncertainty from only a subset of parameters and data inputs, some of which are not used in the Skog (2008) methods (i.e., parameter for increase rate in HWP production and trade from 1900–1961). The Skog et al. (2004) analysis does not account for uncertainty elements that are accounted for in 95% confidence intervals in Skog (2008), including (1) carbon in housing in 2001; (2) fraction of solid wood and paper products from imports; and (3) export carbon storage rate as a fraction of the storage rate for similar U.S. products. Neither publication accounts for uncertainty from elements like (1) fraction of products recovered for compost or burning; (2) fraction of paper or solid wood products sent to dumps rather than landfills; and (3) fraction of pulp from non-wood fiber and imported woodpulp. We were not able to investigate these additional potential sources of uncertainty due to time and resource constraints.

RESULTS

Table T-10. RESULTS – Contributions to uncertainty for harvested wood products in use and in waste disposal sites

Variable held constant	Range of 95% confidence interval (MMT CO_2e)	Contribution to uncertainty (%)	Contribution to uncertainty (MMT CO_2e)
None (all vary)	37.6	–	–
Solid wood product (SWP) data	– [a]	30.5	11.5
Paper data	– [a]	10.2	3.8
SWP conversion to carbon	– [a]	28.8	10.8
Paper conversion to carbon	– [a]	8.5	3.2
SWP discard rate	– [a]	5.1	1.9
Paper discard rate	– [a]	3.4	1.3
Decay rate in solid waste disposal sites	– [a]	5.1	1.9
SWP decay limit	– [a]	1.7	0.6
Paper decay limit	– [a]	6.8	2.5

a) Not reported in Skog et al. (2004).

DISCUSSION

Though Skog et al. (2004) and Skog (2008) are not completely consistent in methods and uncertainty estimation, the total uncertainty estimated in both papers is similar, and both are similar to reported NGHGI uncertainty for HWPs. The three factors accounted for in Skog (2008) uncertainty but not in Skog et al. (2004) therefore likely account for very little uncertainty. However, we cannot infer how much additional uncertainty might be contributed when accounting for uncertainty from factors not assessed in either paper. The final results of this project show that HWP elements are some of the top 10 most impactful factors in determining total forest carbon flux uncertainty, so updated analysis of HWP uncertainty that accounts for a broader range of uncertainty elements would be useful.

2.6 N_2O from N additions to forest soils

NGHGI METHODS

Synthetic nitrogen fertilizers applied to U.S. forest soils result in direct and indirect N_2O emissions (0.5 MMT CO_2e), which are estimated using a Tier 1 approach in which the area of trees receiving N fertilizer is multiplied by estimated application rates from the literature. Indirect N_2O emissions are calculated by first determining the fraction of N volatilized, leached, and runoff, using IPCC default factors. This amount is then multiplied by other IPCC default factors to determine the total of N volatilized and N leached and runoff. Uncertainty is quantified using simple error propagation and stems from the interactions of variables that are unrepresented by the IPCC methodology – including pH, temperature, and soil moisture content – which result in N_2O emissions, and the omission of N_2O emissions from organic N fertilizers. There is also uncertainty in the IPCC emission factors, as well as the area of forest land estimated to receive fertilizer and fertilization rates, which are estimated in accordance with expert knowledge.

DISCUSSION

Because of the small contribution of N_2O fluxes from N additions to forest soils to total GHG flux (Table T-11), we did not undertake further uncertainty attribution analysis beyond what is reported in the NGHGI (2018).

Table T-11: RESULTS – Contributions to uncertainty of N_2O fluxes from N additions to forest soils

Variable held constant	Range of 95% confidence interval (MMT CO_2e)	Contribution to uncertainty (%)	Contribution to uncertainty (MMT CO_2e)
None (all vary)	1.08	–	–
Direct N_2O Fluxes	0.40	90	0.97
Indirect N_2O Fluxes	1.00	10	0.11

2.7 CO_2, CH_4, and N_2O from drained organic forest soils

NGHGI METHODS

CO_2, CH_4, and N_2O emissions from drained organic soils in forests (0.9 MMT CO_2e) are calculated using Tier 1 methodology. There are three types of emissions: (1) direct emissions primarily from mineralization; (2) indirect/off-site CO_2 emissions from dissolved organic carbon in drainage waters; and (3) emissions from peat fires on organic soils. Using FIA and SSURGO data, area of drained organic forest soil is estimated and multiplied by IPCC default emission factors for CO_2, CH_4, and N_2O. Estimation uncertainty of drained organic soil forest area and IPCC emission factor uncertainty is combined through error propagation to estimate the 95% confidence interval reported in the NGHGI (2018).

DISCUSSION

Due to the small contribution of drained organic soil CO_2, CH_4, and N_2O to total LULUCF GHG flux (Table T-12), we did not perform further uncertainty attribution analysis beyond what is reported in the NGHGI (2018).

Table T-12: RESULTS – Contributions to uncertainty for CO_2, CH_4, and N_2O from drained organic forest soils

Variable held constant	Range of 95% confidence interval (MMT CO_2e)	Contribution to uncertainty (%)	Contribution to uncertainty (MMT CO_2e)
None (all vary)	0.55	–	–
CO_2	0.22	87.3	0.48
CO_2 dissolved	0.54	2.6	0.01
CH_4	0.55	0.0	0.0
N_2O	0.51	10.1	0.06

3 Croplands and Grasslands

3.1 Carbon stock change, N_2O, and rice CH_4 on DayCent soils

NGHGI METHODS

The NGHGI cropland and grassland sections, along with agricultural soil management and rice CH_4, use a combination of Tier 1, 2, and 3 methods to estimate fluxes of CO_2, N_2O, and CH_4 from cropland and grassland soils and nitrogen inputs. The U.S. Tier 3 approach, which covers 78% of managed U.S. cropland and grassland soils, utilizes DayCent, a biogeochemical soil model (NGHGI 2018). The soils not covered by Tier 3, including federal grasslands, shaley and gravelly soils, and minor crop types with insufficient data to parameterize DayCent, are calculated with simpler Tier 1 and Tier 2 methods which are based on IPCC (2006, 2019) equations and parameters.

Data inputs to DayCent are primarily sourced from the National Resources Inventory (NRI), a statistically-based survey of non-federal lands in the conterminous U.S. and Hawaii. Land use and management data – including details on crop type, irrigation, and soil attributes – are collected from NRI survey locations. NRI survey locations are classified as Cropland Remaining Cropland, Land Converted to Cropland, Grassland Remaining Grassland, or Land Converted to Grassland, if they have been converted for at least 20 years, using land use histories from 1978.

NRI data was initially collected in five-year cycles beginning in 1982, shifting to annual collection in 1998. They have been collected up until 2012, and the subsequent years following have used a "surrogate data" method to extrapolate 2012 data through 2016 – this means a linear relationship is calculated between GHG fluxes and annual observable data like commodity statistics and weather, and this linear relationship is used to estimate fluxes in years without NRI data, using the annual observable data. Note that the NGHGI (2018) is not explicit about which surrogate data are used for each GHG flux, and uncertainty stemming from the surrogate data estimation is not reported separately from DayCent uncertainty, so it is difficult to understand the impact of lacking NRI data on overall GHG flux uncertainty.

Additional DayCent inputs are obtained from various sources including: net primary productivity data from the NASA-CASA MODIS Enhanced Vegetation Index, tillage data from Conservation Technology Information Center (CTIC), fertilizer use and rates by crop type from USDA Economic Research Service, manure data from the USDA Natural Resources Conservation Service, daily weather data from the PRISM Climate Group, and soil attributes from the SSURGO Database. These inputs all have varying levels of uncertainty.

DayCent output uncertainty is driven by three components (Annex 3 of the NGHGI 2018; Ogle et al. 2010; Ogle et al. 2003):

(1) **Structural uncertainty**: Uncertainty attributed to DayCent model structure and parameterization. This represents at least 70-90% of DayCent output uncertainty.
(2) **Input uncertainty**: Uncertainty in the activity and management data inputs, such as crop type or land-use type, land area of each land-use/management type, fertilization rates, and tillage practices. Data primarily comes from the NRI, as well as the aforementioned sources.

(3) **Scaling uncertainty**: Uncertainty in the accuracy of land stratification and total land area estimates for each land-use/management type. This represents a minor fraction of total uncertainty, and is estimated from the NRI.

To calculate the Tier 3 95% confidence intervals for each GHG flux estimate, all three sources of variance are accounted for (Table T-13).

First, input uncertainty and structural uncertainty are combined through Monte Carlo analysis. Variances for some (but not all) model inputs are used in the Monte Carlo. Thus, some data inputs, such as weather and soils data are considered to have zero uncertainty. To calculate structural uncertainty, DayCent fixed and random effect variances are estimated by regressing DayCent results on empirical soil GHG emissions measurements. Input and structural variances are run through a Monte Carlo analysis together, estimating 100 results for each NRI data point, of which there are over 670,000 representing agricultural land throughout the United States. Each Monte Carlo replicate is area weight-summed across the country to find national soil GHG emissions for each replicate, then the model input/structure variance is estimated by averaging the squared deviation of these summed replicates from the national mean.

Second, scaling uncertainty is calculated as the average variance of GHG emissions estimates across NRI strata (the average NRI point deviation from mean GHG emissions within each land use/management strata, averaged across strata). Scaling variance plus model input/structure variance is assumed to equal total variance, which is used to estimate the total 95% confidence interval for each GHG flux estimate for each land use/management type.

As noted above, a linear regression using surrogate data, predictor variables that explain trends in the emission patterns, with autoregressive moving average errors is used to extrapolate 2012 emissions data to 2016, the most recent year of the NGHGI (2018). This regression contributes additional uncertainty to the 2013-2016 calculations.

Table T-13: Cropland and grassland Soil CO_2, N_2O, and CH_4 flux estimates and uncertainties, Tier 3 (NGHGI 2018)

		2016 Flux Estimate (MMT CO_2e)	**Lower/Upper Bound (MMT CO_2e)**	**Lower/Upper Bound (%)**
Mineral C stock change	Cropland remaining Cropland	-36.3	-80.2 / 7.5	121
	Land converted to Cropland	14.6	-3.5 / 32.7	124
	Grassland remaining Grassland	-4.2	-44.8 / 36.3	958
	Land converted to Grassland	-8.6	-17.4 / -0.3	103
Soil N_2O emissions*	Direct	237.6	199.2 / 276.1	16
	Indirect	45.9	16.0 / 116.8	65 / 154
CH4	Rice cultivation	11.9	7.7 / 16.2	36
Tier 3 Total		260.9	171.4 / 350.4	34

*Tier 3 total uncertainty reported here is calculated by error propagation, assuming normal distribution and independence for all Tier 3 categories (for non-symmetric categories the average error bar is used to estimate a symmetric standard error). Negative values indicate CO_2 sequestration. See Section 3.2 for Tier 1 and 2 uncertainties. *Soil N_2O emissions are quantified through a combination of Tier 3 and Tier 1 approaches. Direct N_2O emissions for DayCent soils are estimated with a Tier 3 approach, and DayCent outputs for N volatilization and NO_3 leaching/runoff are combined with Tier 1 factors to derive indirect emissions. For soils not covered by DayCent, an exclusively Tier 1* *approach is used for both direct and indirect N_2O emissions. NGHGI N_2O results are not reported by Tier 3 vs. Tier 1. Because DayCent covers 91% of direct N_2O emissions, all N_2O emissions are listed as Tier 3, for simplicity.*

PROJECT METHODS

Our objective was to use consistent methods for estimating and attributing uncertainty across all the NGHGI sections in our scope, with the ideal approach being full replication of inventory methods and using the contribution index equation to estimate uncertainty attribution. Unfortunately it was not possible to do this for the cropland and grassland sections, both due to the complexity of the DayCent model and due to the confidential nature of the NRI dataset. This made it impossible to replicate Tier 1, 2, or 3 components of the cropland and grassland sections.

Our alternative method for Tier 3 uncertainty attribution was to issue an expert elicitation to rank all cropland and grassland elements of uncertainty. We discuss our alternative methods for Tiers 1 and 2 below in Section 3.2, Carbon stock change and N_2O in non-DayCent soils. The full survey can be viewed here: https://www.surveymonkey.com/r/LULUCFinventory. The objective of the Tier 3 expert elicitation was two-fold: 1) to quantify the uncertainty associated with each data and model element used to calculate U.S. mineral soil GHG fluxes on croplands and grasslands (note that organic soils are not included in Tier 3), and 2) to rank priority research, model development, model inter-comparison, and empirical data-generating activities for reducing uncertainty in national soil GHG emission estimates. The elicitation was split into two parts, with each addressing one of the objectives.

Participation in Section 1 required knowledge of Century/DayCent or similar biogeochemical soil models, and IPCC accounting. Experts were asked to confirm that they possessed this knowledge before completing Section 1. It was divided into three prompts.

In Section 1, Prompt 1, participants were asked to provide their best estimate of the percentage contribution of various model inputs, model structure, and other sources of uncertainty, to total estimated uncertainty for soil GHG emissions estimates. They were asked to consider 11 DayCent inputs and DayCent processes/parameters, including: manure and organic fertilizer applications, tillage, plant growth and phenology, and methanogenesis. To aid the experts in their elicitation, each element was hyperlinked to a pop-out box that further elaborated on how that specific element played a role in DayCent calculations and how it could contribute to uncertainty. For reference, participants were provided a description of how uncertainty is estimated for Tier 3 calculations (similar to the description above) and a table of cropland and grassland soil CO_2, N_2O, and CH_4 flux estimates and uncertainties by tier. Experts were provided an example to guide their responses: if a participant believed that one of the elements, for example fertilization management, contributed 10% to total uncertainty, s/he was suggesting that fertilization management represented about 8.95 MMT CO_2e of the total Tier 3 89.5 MMT CO_2e 95% confidence interval in one direction of the mean. Uncertainty effects were assumed to be symmetric about the mean and while experts could indicate their beliefs that the elements had a non-symmetric effect, none did so. Experts were instructed that the total percentage estimates were to sum to 100% or less.

In Section 1, Prompt 2, experts were asked to complete a similar exercise, but for elements that hadn't been included in the calculation of the cropland/grassland Tier 3 95% confidence interval. These were elements that had been considered "certain" for purposes of estimating the 95% confidence interval in the NGHGI (2018). Participants could attribute any percentage to these elements, as long as their estimates reflected the additional uncertainty that was contributed to the 95% confidence interval, had their true variance been incorporated into the analysis. Again, experts were provided an example to guide their responses: if a participant believed that the first listed element, "Soil properties," contributed 10% to the total uncertainty, this meant it represented an expansion of the current 95% confidence interval by 5% (of the mean, in MMT CO_2e) in each direction (upper limit and lower limit), in accordance with a symmetric distribution. This would suggest that *Cropland Remaining Cropland*, for instance, added 4.28 MMT CO_2e above and below the current uncertainty range.

In Section 1, Prompt 3, we asked experts to rate the importance of the planned/suggested improvements, as described in the NGHGI, for cropland/grassland Tier 3 estimates, and their ability to reduce U.S. soil GHG emissions uncertainty or to address omitted fluxes. Experts could select one of five responses – Not important, Slightly important, Important, Very important, and Extremely important – for each planned/suggested improvement.

Any expert in soil science and GHG measurement and accounting was encouraged to complete Section 2. We stressed that a knowledge of Century/DayCent was not required for this section. Participants were asked to rank the importance of various research, model development, intermodel comparison, and data-generating activities, specifically with regard to reducing uncertainty in national U.S. soil GHG emission estimates. The elements available for ranking in this section were identified through an extensive literature review of 52 papers. Two literature searches were conducted – one focused on CO_2 fluxes in cropland and grassland landscapes, and the other on CH_4 and N_2O fluxes – using search terms specifically selected to generate relevant results, such as "model" and "additional research." The search was limited to papers published between 2010 and 2018. Papers were ranked according to the total number of citations, and reviewed in full if they discussed soil CO_2, N_2O, and/or CH_4 findings, research needs, or modeling for GHG fluxes on croplands or grasslands. Additional papers recommended by stakeholders were also reviewed, summing up to a total of 58.

Similar to Section 1, Section 2 was also divided three prompts, asking about priorities in 1) primary soil research; 2) soil model development and intermodel comparison; and 3) empirical data needs, respectively. For each prompt, participants were asked to rate the importance of the various listed literature recommendations specifically with respect to how effectively they could improve soil GHG emissions for national GHG accounting in the United States.

Expert review and participation

Prior to distribution, the expert elicitation was reviewed by the NGHGI leads for croplands and grasslands to ensure accuracy and usefulness. The survey was then distributed through three channels – to the primary authors of the 58 papers reviewed, to USDA and EPA scientists that had previously been contacted for various parts of this project or that had been listed as contributors to the cropland and grassland section of the NGHGI, and to the listserv of the International Soil Carbon Network. In sum, the survey reached the inboxes of 984 people, the majority of which came from the ISCN listserv (879 individuals), who were provided three weeks to complete the survey.

Response rate was more muted than hoped. Of the 47 individuals clicked into the survey, 19 provided responses. Seven experts completed some or all of Section 1 (not all questions required responses), and 19 completed Sections 2. The 19 that completed Section 2 included the seven from Section 1. We hypothesize that there may have been a low response rate for a few reasons: 1) Section 1 was very specific and only those with deep knowledge of Century/DayCent or other similar biogeochemical models, and IPCC accounting were requested to participate; 2) Section 2 was comprehensive and if respondents were not familiar with the breadth of soil science discussed, they may have been deterred from participation; 3) the majority of experts on the primary author list were academics and scientists in other countries, and perhaps were not as invested in providing feedback that would benefit the national greenhouse gas inventory for the United States. Despite this, some consistent themes emerged, particularly around the need for more data and a better understanding of the N_2O cycle.

Of those who responded, most had expertise in the fields of soil science (87%), biogeochemistry (67%), and the carbon cycle (67%). 53% worked in academia, followed by 33% in government, and the remainder in NGO or private sector.

RESULTS

Section 1

The results for Section 1, Prompts 1 and 2 are displayed below in Table T-14 and Table T-15. Values reflect the averages of all responses.

Table T-14: RESULTS - Contributions to uncertainty for Tier 3 cropland and grassland soils

Category	Element	Contribution to uncertainty (%)	# of responses
DayCent processes and parameters	Organic matter formation and decomposition	17	5
DayCent processes and parameters	Nitrification and denitrification processes	16	5
DayCent inputs	Manure and other organic fertilizer applications	15.5	5
DayCent inputs	Tillage (conventional, reduced, no-till)	15.5	5
DayCent inputs	Fertilization management	14.5	5
DayCent processes and parameters	Soil and water temperature regimes by layer	10.4	5
DayCent processes and parameters	Plant growth and phenology	9.5	5
DayCent inputs	Enhanced Vegetation Index (EVI) data	7.7	5
DayCent processes and parameters	Methanogenesis	5.9	5
Other	Surrogate data	4.7	5
Other	Expansion factors	2	5

Table T-15: RESULTS - Average Prompt 2 responses – greatest contributors to Tier 3 uncertainty, not included in reported 95% confidence interval

Category	Element	Contribution to uncertainty (%)	# of responses
All land use and GHG flux categories	Soil properties	17.5	5
Cropland Remaining Cropland and Land Converted to Cropland	Leaching, runoff, and volatilization	16	5
Grassland Remaining Grassland	Grazing intensity	8.5	5
Cropland Remaining Cropland and Land Converted to Cropland	Irrigation	8	5
Cropland Remaining Cropland and Land Converted to Cropland	Harvest, variable residue removal	7.4	5
Cropland Remaining Cropland and Land Converted to Cropland	Flooding/drainage for rice cultivation	6.5	5
Cropland Remaining Cropland and Land Converted to Cropland	Crop types	6.5	5
All land use and GHG flux categories	Daily weather data	6.25	5
Grassland Remaining Grassland	Burning (grasslands)	4.7	5
Cropland Remaining Cropland and Land Converted to Cropland	Organic amendments for rice cultivation	5.75	5
Cropland Remaining Cropland and Land Converted to Cropland	Crop sequences (rotation)	5.4	5
All land use and GHG flux categories	NRI time series	2.7	5

These results from Prompt 1 and 2 indicate participating experts believed much of the uncertainty can be attributed to the following:

(1) **DayCent methods for representing organic matter dynamics and utilizing soil properties**. "Organic matter formation and deposition" (17% of Tier 3 uncertainty) references the soil organic C and N dynamics assessed for the top 30 cm of the soil profile. DayCent represents organic C and N stocks by two plant litter pools and three soil pools that exhibit increasing recalcitrance and humification. There is increasing literature debate about the ability of such a categorical "pool" structure to represent soil processes. "Soil properties" (17.5% of additional uncertainty) references the primary soil input variables in DayCent – soil texture and natural drainage capacity. These data are collected through field measurements – which may exhibit uncertainty due to errors in data mapping, collection, and processing – and aerial photography and remote sensing imagery – which are approximations of ground data.

(2) **N_2O inputs and soil process**. The uncertainty associated with "Nitrification and denitrification processes" (16% of Tier 3 uncertainty) stems from the simulation of nitrification and denitrification from factors like water filled pore space, which vary; nitrification is also only calculated for the top 15 cm. "Manure and other organic fertilizer applications" (15.5% of Tier 3 uncertainty), references estimates of organic fertilizers which may have uncertainty due to assumptions such as application type, or land area amended with manure, "Leaching, runoff, and volatilization" (16% of additional uncertainty), references the amount of N lost through these processes, though there is variability in fertilizer and organic amendment activity data. There is also lack of measurement data on the volatilization of N gases that contribute to indirect soil N_2O emissions, and indirect N_2O emissions are not always measured. "Grazing intensity" (8.5% of additional uncertainty) uses an input schedule file to simulate the timing of grazing and other management activities, though this is only an estimation.

(3) **"Tillage"** (15.5% of Tier 3 uncertainty). Three tillage practices are considered in the LULUCF inventory: conventional, reduced, and no-till. The most recent data on U.S. tillage activity is from 2004 (Conservation Technology Information Center 2004). The definition of tillage practices and equipment is based on the 1995 USDA Cropping Practices Survey. Thus uncertainty stems from changes in uptake rates of various tillage practices since 2004 and changes in tillage practices and technologies. There is also a lack of direct data on how many no-till fields are under continuous no-till vs. intermittent tillage. This is estimated through expert elicitation.

Prompt 3 asked about the importance of planned or suggested improvements, as described in the NGHGI (2018). We assigned each of the response choices a numerical value from 1-5: Not important = 1, Slightly important = 2, Important = 3, Very important = 4, and Extremely important = 5, and analyzed the results based on the average of all responses. Importance was again placed on data needs and a better understanding of N_2O fluxes: "Additional experimental site studies" which received a 4 and could improve model structural uncertainty through additional calibration; "Improved representation of drainage and freeze and thaw cycles" which also received a 4 and could potentially improve model accuracy; and "Improved representation of emissions from small grain cropping" (3.8) which would help reduce DayCent's overestimate of emissions from small grain cropping. Prompt 3 results are shown in Table T-16.

Table T-16: RESULTS - Prompt 3 – importance of planned/suggested improvements

Element	Rating	# of responses
Improved representation of drainage and freeze-thaw cycles	4	7
Additional experimental site studies	4	7
Improved representation of emissions from small grain cropping	3.8	7
Improved simulation of plant production	3.6	7
Soil organic stock changes to a depth beyond 30cm	3.4	7
Represent the influence of nitrification inhibitors and slow-release fertilizers on N_2O emissions	3	7
Incorporation of Conservation Effects Assessment Project data	2.8	7
Include above-ground biomass C changes	2.8	7
Crop residue burning	2.4	7
Missing fluxes of soil GHG emissions from Alaska and Hawaii	2	7

Section 2

In this section, there were up to 19 responses per query (not every respondent completed the entire section). The average ranking for each of the 60 research, model development, or empirical data improvement needs was calculated and can be found in the Appendix below, and the top 10 most highly ranked needs are displayed in Table T-17. In the top 10 most highly rated needs, 7 out of 10 scored a 4 (Very important) or above, which were nearly all related to model construction/validation needs, or building collaborative research/monitoring networks. This is unsurprising given that the NGHGI indicates that upwards of 80% of total cropland and grassland Tier 3 uncertainty stems from the structure of the DayCent model (Ogle et al. 2010, Annex 3.B. of the NGHGI 2018). Consistent with the findings from Section 1, all three of the primary soil research needs that were rated in the top 10 were related to the N cycle.

Table T-17: RESULTS - Priority research, model, and data needs, rated by importance

Category	Research Need	Rating	# of responses
Empirical data needs	Build research site networks of N_2O and CH_4 soil fluxes and soil C measurements resulting from a diverse range of management activities (Schmidt et al. 2011).	4.26	16
Empirical data needs	Establish a national soil monitoring network to produce for a full and consistent dataset of soil carbon measurements over time (Schmidt et al. 2011; Spencer et al. 2011).	4.26	16
Soil model development and intermodel comparison	Improve model validation with updated comparisons to empirical regression models that are based on field experiments (Brevik et al. 2015; Kuzyakov 2010; Paustian et al. 2016; Schmidt et al. 2011; Stockmann et al. 2013).	4.18	17
Soil model development and intermodel comparison	Increase collaboration among model developers, shifting to a community-centered, open-source approach and integrating databases and computational tools (Paustian et al. 2016; Schmidt et al. 2011)	4.09	17
Primary soil research	Influence of microbial activity – and other physicochemical and biological influences – on decomposition of organic matter/carbon, nitrogen and phosphorous cycling (Conant et al. 2011; Kuzyakov 2010; Schmidt et al. 2011; Schimel & Schaeffer 2012).	4.00	19
Soil model development and intermodel comparison	Expand model inter-comparison programs (such as AgMIP) to identify cross-cutting sources of uncertainty and opportunities for model improvement and cross-pollination.	4.00	17
Empirical data needs	Obtain additional measurements of N_2 production and losses from denitrification to clarify optimal N_2 / N_2O ratios for both modeling purposes and proper fertilizer management (Bakken & Frostegård 2017; S. DelGrosso, personal communication, October 1, 2018; Well et al. 2018).	4.00	16
Soil model development and intermodel comparison	Reconcile bottom-up, process-based accounting of N_2O fluxes with newer top-down methods (e.g., atmospheric inversions) that capture N cycling from the global and regional perspective (Butterbach-Bahl 2013; Chen et al. 2016; DelGrosso et al. 2008; S. DelGrosso, personal communication, October 1, 2018; Nevison et al. 2018).	3.91	17
Empirical data needs	Obtain additional experimental data on above-ground N uptake or direct measurements of N_2O for cross-site optimization/better validation of large scale model estimates of soil N_2O fluxes (S. DelGrosso, personal communication, October 1, 2018; Ehrhardt et al. 2018; Reay et al. 2012; Van Groenigen et al. 2010).	3.91	16
Primary soil research	Contribution of biochar feedstock type, production temperature and process, application rate, interactions with N sources, and more to the observed reduction of soil N_2O emissions through biochar application (Cayuela et al. 2014).	3.83	18

DISCUSSION

Across Section 1 and Section 2, themes emerged around the need for more data and a better understanding of the N_2O cycle. In Section 1, respondents indicated that DayCent organic matter formation representation, accuracy of soil data (both from the methods used to collect data as well as the depth to which the soils are sampled), and an incomplete accounting and understanding of the N cycle are major sources of uncertainty. This included the need to more accurately capture grazing intensity and the impact of manure on the N cycle, whether it be through nitrification and denitrification or timing of organic fertilization. One respondent noted that, “Timing of fertilization is a scheduling problem with potential impacts on N_2O estimates. Our inability to represent fertilizer placement also contributes to uncertainty. Decomposition, especially at lower temperatures, can be problematic. DayCent's representation of the N cycle is complicated.” Another respondent echoed that sentiment, noting that, “We know manure is applied heavier around these spots, and the inventory is blind to this. We need better data on spatial manure applications, heavy manure N applications (and resulting high N_2O) are being ignored due to this.”

With regard to planned/suggested improvements, one of the highest ranked improvements asked for a more accurate freeze-thaw representation related to the N_2O cycle. Another highly ranked improvement was, as described by one respondent: “resources for model improvement and evaluation using available observational data sets.” This sentiment was echoed repeatedly in Section 2, with the top rated priority needs centered around data and a desire to collect more comprehensive, consistent, and cohesive CO_2, N_2O, and CH_4 soil measurements, and to make these measurements more transparent and publicly available. Respondents also noted that model developers themselves could benefit from more collaboration, since, as one individual noted, “data is not shared enough and large scale efforts and comparisons are underfunded.” Of the single primary research need rated as “Very important” – “Influence of microbial activity – and other physicochemical and biological influences – on decomposition of organic matter/carbon, nitrogen and phosphorous cycling” – one respondent noted, “We simply don't understand the dynamics - I suspect that microbial processes are 5, and until we unravel those drivers, we will struggle to make progress.”

There were also consistent areas of general indifference, namely any uncertainties that could be rectified in the future, like time series inconsistencies (intermittent updating of NRI data), extrapolated data (expansion factors) or unmeasured soil GHG fluxes from Alaska and Hawaii, and any research needs around biochar (one individual noted, “Biochar and compost amendments benefits are over stated. Too many publications would not pass a simple 'back of envelope' calculation in regard to their benefit.”). Methane fluxes were also of low interest, likely due to the limited rice and other methane producing systems in the U.S. All of these areas either had a very low percentage of uncertainty attributed to them, or they were rated of the lowest importance, between a 2 and a 3 (Slightly important and Important).

Overall, the themes that emerged from the LULUCF expert elicitation were clear, but based on a small sample population of responses. It is difficult to know how well these responses reflect the opinions of the broader scientific community, but they do appear to be consistent with available data from the literature and the NGHGI itself. Identifying uncertainty is inherently challenging – as one respondent noted, “we will always be limited by the difficulty of creating a generalized model that can represent the variability and processes of the natural world. DayCent sees the world as flat.” The findings from this expert elicitation are a first step at identifying the key areas that soil scientists believe can help to reduce uncertainty, and improve overall model development.

3.2 Carbon stock change and N_2O in non-DayCent soils

NGHGI METHODS

There are several GHG flux categories in croplands and grasslands that follow Tier 1 or Tier 2 methodology because it is not possible to source all the input data required to utilize DayCent. These categories are: direct N_2O, mineral soils; CH_4 rice cultivation; soil organic C stock change, mineral soils; soil organic C stock change due to biosolids, mineral soils; soil organic C stock change, drained organic soils; direct N_2O, organic soils; indirect N_2O volatilization and; indirect N_2O, leaching and runoff.

The U.S.-specific data for Tier 2 calculations come from various sources including: the Conservation Technology Information Center (CTIC) which provides classification of cropland area by tillage practice; the literature which describes U.S. carbon stock change factors and manure N amendments over time (Ogle et al. 2003; Edmonds et al. 2003, respectively); and reference carbon stocks which are estimated using the National Soil Survey Characterization Database.

Uncertainty is generally determined through a Monte Carlo in which carbon fluxes are estimated 50,000 times, and PDFs for U.S.-specific stock change factors, reference C stocks, and land use activity data.

Table T-18: Cropland and grassland soil CO_2, N_2O, and CH_4 flux estimates and uncertainties, Tiers 1 and 2 (NGHGI 2018)

		2016 Flux Estimate (MMT CO_2e)	Lower/Upper Bound (MMT CO_2e)	Lower/Upper Bound (%)
Organic and mineral C stock change	Cropland remaining Cropland	26.4	21.9 / 30.9	17
	Land converted to Cropland	5.7	2.6 / 8.8	53
	Grassland remaining Grassland	2.6	0.9 / 4.3	66
	Land converted to Grassland	-2.0	-4.1 / 0.1	107
CH_4	Rice cultivation	1.8	0.8 / 2.8	55
Tier 1 and 2 Total		34.5	28.3 / 40.7	18

Negative values indicate CO_2 sequestration.

PROJECT METHODS

Similar to the challenges for Tier 3 cropland and grassland calculations, we were not able to replicate Tier 1 and 2 methods and perform our own contribution index analysis. The calculation methods are simple, but the NRI data (a primary input) is not publicly available. As an alternative, we used the contribution index results from Ogle et al. (2003) and applied these percentages to NGHGI (2018) GHG flux values.

Ogle et al. 2003 runs their contribution index over the following elements of uncertainty for Tier 1 and 2 calculations: land use (NRI data), tillage practices (CTIC data), reference carbon stocks, input factor, tillage factor, land use change factor, improved pasture, and carbon loss rate on organic soils.

To use the Ogle et al. (2003) percentages, first we combined all Tier 1 and 2 cropland and grassland emissions estimates, and their respective 95% confidence intervals, using error propagation (Table 8). This step was required because the Ogle et al. (2003) percentages are reported in aggregate, not for individual category's emissions estimates. Then we multiplied the contribution index for each Ogle et al.

2003 element by the magnitude of the total 2016 95% confidence interval from Table T-18. This allowed us to derive the magnitude of uncertainty contribution in terms of MMT CO_2 for each element.

RESULTS

The highest contribution to uncertainty stemming from carbon loss rate from organic soils (4.39 MMT CO_2e), followed by land use change factor and tillage factor (3.43 MMT CO_2e for each) (Table T-19).

Table T-19: RESULTS - Contributions to uncertainty for Tier 1, 2 cropland and grassland soils

Input	Contribution to uncertainty (%) from Ogle et al. (2003)	Contribution to total uncertainty (MMT CO_2e)
Land use	4.6	0.57
CTIC	3.1	0.38
Reference stock	<1.0	0.01
Input factor	<1.0	0.01
Tillage Factor	27.7	3.43
Land use change	27.7	3.43
Improved pasture	1.5	0.19
Carbon loss rate, organic soils	35.4	4.39
Total	100	12.42

DISCUSSION

There is opportunity to further refine this analysis for greater granularity and applicability to current inventory methods. The contribution index values from Ogle et al. (2003) were only calculated for a subset of land use and management activities. Uncertainties are also present in fertilization management – specifically around manure amendments, biosolid amendments, residue N inputs, wetland reserves, emission factors for various soil types, and land area. Note that we do not include any N_2O Tier 1 estimation in this analysis because N_2O results are not reported by Tier 3 vs. Tier 1 in the NGHGI so we assume they all fall under Tier 3 for simplicity (Tier 3/DayCent covers 91% of U.S. direct soil N_2O emissions).

This analysis is also unable to dissect uncertainty attribution across different components of the Tier 1 and 2 estimates – despite there being nine distinct land types, each subject to particular C stock change equations (as mentioned earlier – e.g., indirect N_2O from leaching and volatilization). Additionally, this analysis is based on data that is over 15 years old, and calculations that were performed three years before Century/DayCent was first used for Tier 3 cropland and grassland accounting, so the contribution index results from Ogle et al. (2003) are derived from all U.S. soils, not the subset of soils currently handled under Tier 1 or 2. A new analysis replicating the level of detail we were able to achieve in other sections would have been ideal but unfortunately was not possible with available data.

3.3 Non-CO_2 from grassland fires

NGHGI METHODS

The NGHGI quantifies CH_4 and N_2O emissions from grassland fires for 1990–2014 using the same general equation as is applied for forest fire emissions (Equation 3). This methodology involves the multiplication of four factors:

(1) Burned area
(2) Fuel availability (mass of dry matter available per unit area)
(3) Combustion factor (mass of dry matter burned per mass of dry matter available)
(4) Emission factor (mass of CH_4 or N_2O emitted per mass of dry matter burned)

Grassland fire emissions reported by the NGHGI account for the combustion of herbaceous biomass on managed grasslands in the conterminous United States. The NGHGI does not quantify emissions from the burning of woody biomass on grasslands, nor does it quantify emissions from grassland fires in Alaska. Estimates of grassland burned area are derived by combining burned area estimates from the Monitoring Trends in Burn Severity (MTBS) dataset (MTBS Data Summaries 2015) with estimates of managed grassland area from (1) the 2012 National Resources Inventory for non-federally owned areas (Nusser and Goebel 1997; USDA–NRCS 2015) and (2) the National Land Cover Dataset (NLCD) for federally owned areas (Fry et al. 2011; Homer et al. 2007; Homer et al. 2015). Default factors from IPCC (2006) are applied for fuel availability (4.1 metric tons dry matter per ha) and emission factors (2.3 g CH_4 emitted per kg dry matter burned and 0.21 g N_2O emitted per kg dry matter burned). A combustion factor of 1 is assumed; that is, it is assumed that all available herbaceous biomass is completely combusted. The global warming potentials for CH_4 and N_2O on 100-year time horizons (IPCC 2007) are used to convert non-CO_2 emissions to CO_2 equivalents.

Because the input factors for this equation were not recalculated for years beyond 2014 in the NGHGI that covers 1990–2016, grassland fire emissions for years beyond 2014 are quantified using linear regression with autoregressive moving-average (ARMA) errors. The NGHGI does not specify how many lags are included in the ARMA model or what surrogate data is included, if any. The 95% confidence interval reported in the NGHGI (2018) is derived using this regression model; this is distinct from the uncertainty estimation for non-CO_2 emissions from forest fires, which utilizes Monte Carlo iterations and the distributions of the underlying inputs.

PROJECT METHODS

Unlike the NGHGI, we quantify the 95% confidence interval for non-CO_2 emissions from grassland fires using Monte Carlo iterations (n=1,000,000) based on Equation 3. We separately quantify the 95% confidence intervals for CH_4 and N_2O emissions from grassland fires and additionally estimate the percent contribution to uncertainty from each of three uncertain parameters: grassland burned area, fuel available, and emission factor. We focus our calculation on year 2014 since this is the most recent year for which burned area estimates are available in the NGHGI (2018). The NGHGI reports total grassland burned area in 2014 for the conterminous United States as 1,659,000 ha. Following the burned area parameter for forest fires, we assume that grassland burned area is likewise normally distributed with a standard deviation that is 4% of the mean (66,360 ha). Similarly, for the following parameters, we assume the same distribution types for grassland fires as are assumed for forest fires: (1) emission factors (normal distributions, truncated at zero) and (2) fuel availability (lognormal distribution). The standard error for fuel availability (3.1 metric tons dry matter ha^{-1}) and the standard deviations for the emission factors (0.9 g CH_4 emitted kg^{-1} [dry matter burned] and 0.1 g N_2O emitted kg^{-1} [dry matter burned]) are from IPCC (2006). No uncertainty is attached to the global warming potentials. We assume independence of all uncertain variables in the Monte Carlo analysis. We do not consider the ARMA errors as we focus our calculation on year 2014.

RESULTS

The 2014 estimates and 95% confidence intervals for CH_4 and N_2O emissions from grassland fires are shown in Table T-20. The estimates for 2014 are identical to those reported in the NGHGI (2018) (0.4 MMT CO_2e from CH_4 and 0.4 MMT CO_2e from N_2O). The NGHGI reports uncertainty only for the 2016 estimate. We find slightly larger relative uncertainties in the upper direction (≥225% for 2014 estimate) than the NGHGI reports for the 2016 estimate (145%).

Table T-20: Uncertainty estimates for non-CO_2 emissions from grassland fires

Gas	2014 estimate (MMT CO_2e)	Lower bound [a] (MMT CO_2e)	Upper bound [a] (MMT CO_2e)	Lower bound [b] (%)	Upper bound [b] (%)
CH_4	0.4	0.0	1.3	-100	225
N_2O	0.4	0.0	1.5	-100	275
Total	0.8	0.1	2.7	-88	238

(a) Lower and upper bounds correspond to 2.5th and 97.5th percentiles (95% confidence interval).
(b) The relative uncertainties are calculated as a percentage of the 2014 estimate.

The results of the contribution index analysis, which is based on total non-CO_2 emissions from grassland fires (i.e., total CH_4 and N_2O emissions as CO_2 equivalents), are shown in Table T-21. As we found for forest fires, the fuel availability makes the largest contribution to uncertainty (99%). The burned area and emission factors contribute only negligibly to total uncertainty.

Table T-21: RESULTS - Contributions to uncertainty for non-CO_2 emissions from grassland fires

Variable held constant	Range of 95% confidence interval (MMT CO_2e)	Contribution to uncertainty (%)	Contribution to uncertainty (MMT CO_2e)
None (all vary)	2.52	–	–
Burned area	2.51	0.3	0.0
Fuel availability	0.96	99.1	2.5
Emission factors	2.51	0.6	0.0

DISCUSSION

Total non-CO_2 emissions from grassland fires are likely underestimated since the calculation excludes emissions from: (1) grassland fires in Alaska and (2) combustion of woody biomass on all grasslands. We estimate the non-CO_2 emissions associated with combustion of woody biomass on managed non-Alaskan grasslands in Section 3.5, Omitted GHG fluxes in cropland and grassland.

3.4 Carbon stock change in drained organic cropland and grassland soils

NGHGI METHODS

To estimate organic soil carbon stock changes due to drained organic soils, a Tier 2 methodology is followed, using U.S.-specific carbon loss rates from Ogle et al. (2003) and land area data from the 2012 NRI. These are applied to IPCC default equations, and uncertainty is calculated using a Monte Carlo analysis with 50,000 iterations. A surrogate data method is used to estimate carbon emissions from 2012 to 2016, which also contributes to uncertainty.

DISCUSSION

Due to the small contribution of carbon stock changes from drained organic soils (Table T-22), we did not perform further attribution analysis beyond that reported in the NGHGI (2018).

Table T-22: RESULTS – Contributions to uncertainty for drained organic cropland and grassland soils

Variable held constant	Range of 95% confidence interval (MMT CO_2e)	Contribution to uncertainty (%)	Contribution to uncertainty (MMT CO_2e)
None (all vary)	6.7	–	–
Cropland remaining Cropland	2.4	91.2	6.1
Land converted to Cropland	6.4	6.4	0.4
Grassland converted to Grassland	6.6	1.8	0.1
Land converted to Grassland	6.7	0.6	0.0

3.5 Omitted GHG fluxes in cropland and grassland

The objective of this project is not only to estimate uncertainty attribution of current NGHGI calculations, but also to identify omitted GHG fluxes in the NGHGI. Here we identify four potential omitted fluxes (woody biomass and litter; microbial methane sink; certain sinks and sources on federal cropland and grassland; and other croplands) described in the cropland/grassland NGHGI sections. We describe the methods and results of first order estimates of each omitted GHG flux.

Other Croplands

The NGHGI (2018) notes that emissions from 0.8% of cropland is not accounted for (updated to 0.3% in the 2019 NGHGI), due to limited resources and/or understanding of greenhouse gas emissions from those management systems. According to the NGHGI and the NGHGI team, these omitted areas are aquaculture, Alaska, and the U.S. territories. Per the NGHGI, Alaskan croplands represented 28,700 hectares in 2016, and according to the latest 2013 U.S. Census of Aquaculture, aquaculture represented 289,570 hectares, the most recent data available. These two amount to 318,270 hectares, with the remainder missing cropland found in U.S. territories and possibly other unclassified cropland types. We estimate the omitted flux from Alaskan croplands below in Section 6: Alaska, Hawaii, and U.S. Territories.

Furthermore, note that N_2O from aquaculture is included in Coastal Wetlands Remaining Coastal Wetlands, so aquaculture is not completely omitted from the NGHGI. See more in the Wetlands section of this document below.

Biomass and litter

IPCC guidance calls for the reporting of carbon stock changes in all significant carbon pools in croplands and grasslands. Yet only soil carbon is accounted for in the U.S. NGHGI for croplands and grasslands (except for conversions of forest to cropland or grassland and vice versa). Here we provide a first order estimate of the omitting GHG fluxes from woody biomass and litter on cropland remaining cropland and grassland remaining grassland by focusing on three land cover types on cropland and grassland that have significant woody biomass and, as a result, potential for significant carbon flux:

- Agroforestry
- Fruit and nut orchards
- Woodlands

Our estimates below do not account for carbon loss due to fire, which would need to be accounted for in the NGHGI. Each section below describes the literature review and calculation methods we used to derive annual carbon flux estimates from these land cover types.

AGROFORESTRY

Net carbon emissions from agroforestry across the United States were estimated using land area data from USDA and emission factors from literature. Four types of agroforestry were considered: windbreaks, riparian buffers, alley cropping, and silvopasture. High and low emission estimates were calculated by multiplying land area by per area-per year emissions factors, and applying a legacy effect to all estimates (windbreaks, reported in linear feet by the USDA, were first converted to hectares).

The most recent USDA agroforestry data available is found in the report *Agroforestry: USDA Reports to America, Fiscal Years 2011 to 2012* (USDA 2012). The data is determined by the number of acres that were enrolled in USDA conservation programs. It should be noted, however, that agroforestry established through these programs is only a portion of what occurs in the U.S. and does not include landowners that applied agroforestry without USDA assistance, or those who received assistance before 2008. The USDA report notes specific acreage benefiting from the programs for 2011 and 2012, as well as the total acreage for the period of FY 2008-2012. To estimate the yearly acreage in 2008 to 2010, the acres for 2011 and 2012 were subtracted from the aggregated acres over 2008-2012, and then divided by three. All acre values are subsequently converted to hectares. To further extend the timeline of estimated land area under agroforestry before and after FY 2008-2012, we used budget numbers for three federal conservation programs – the Conservation Stewardship Program (and its predecessor, the Conservation Security Program), Conservation Reserve Program, and the Environmental Quality Incentives Program and derived ratios of total enrolled agroforestry acres for each practice to total conservation budget for 2008 to 2012, the years with known acreage. The average of these ratios (across 2008-2012) for each agroforestry practice were then multiplied by the total budget numbers for the years preceding 2008 and following 2012, providing a set of acreage estimates for 2004 to 2016, as illustrated in Table T-23. Land area in the white boxes represent estimates calculated using the budget ratios; the land area in blue is reported by USDA (with annual estimates derived from the 2008-2012 total acreage and 2011, 2012 annual acreage). For details on this calculation, see the Spreadsheet Appendix.

Table T-23: Reported and estimated hectares of USDA-supported agroforestry practices (USDA 2012)

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Windbreaks	4,754	5,130	5,412	5,506	6,093	6,093	6,093	6,389	5,269	3,990	7,295	7,229	7,787
Riparian	16,202	17,484	18,447	18,766	16,643	16,643	16,643	23,767	31,084	13,597	24,862	24,636	26,539
Alley cropping	227	245	259	263	419	419	419	82	22	191	349	346	373
Silvopasture	128	138	145	148	146	146	146	236	134	107	196	194	209

Blue highlighted cells show annual values reported by/derived from USDA (2012). White cells show values derived from annual federal conservation budgets for 2004-2007, 2013-2016.

Emissions factors for different types of agroforestry practices were sourced from a paper which estimates carbon sequestration potential in the U.S. through a meta-analysis of peer reviewed papers and government documents (Udawatta and Jose 2012). We had initially considered a conservative estimate from Nair and Nair 2003, though in correspondence with the primary author, we were advised that their data was outdated. Thus, the emissions factors from Udawatta et al. (2012) were multiplied by the yearly USDA land area data and estimates over the period of 2004 through 2016 (Table T-24). The paper explicitly notes that its carbon sequestration rates cover aboveground and belowground biomass and soil organic carbon, but it does not explicitly discusses whether dead wood or litter is included in their estimates (although it may be assumed that litter is considered because of the discussion of litter from its list of reviewed papers).

Table T-24: Agroforestry emissions factors from literature (Udawatta and Jose 2012)

Agroforestry practice	Emissions Factor (Mg C ha^{-1} yr^{-1})
Windbreaks	0.96
Riparian buffers	2.6
Alley cropping	3.4
Silvopasture	6.1

It is assumed that even as land area under agroforestry practices officially exit the federal program, they continue to provide carbon sequestration benefits. Legacy effects, or an ongoing discounted sequestration rate, are therefore applied to agroforestry land for all future years after enrollment in federal programs.

To estimate legacy effects, each annual carbon sequestration rate for a given enrolled hectare was discounted at 75% for the initial five years following enrollment, followed by a 50% discount for the remainder of the time series. For example, the carbon sequestration rate for a hectare enrolled in an agroforestry practice in 2004 was 100% of the literature-derived emissions factor in 2004, was discounted by 75% for the years 2005 to 2009, and then at 50% from 2010 onwards. For each year, the total carbon stock changes from all the previous year's legacy effects were summed and then added to any carbon stock change from newly enrolled land area in that year.

Equation 4: Carbon stock change from agroforestry

$$\Delta CO_{2_{it}} = \left[(A_{it} * EF_i) + \left(D_{1-5} \sum_{s=t-5}^{t-1} A_{is} * EF_i\right) + \left(D_{\geq 6} \sum_{s=0}^{t-6} A_{is} * EF_i\right) \right] * \frac{44}{12}$$

Where:

ΔCO_{2_t} = Total carbon stock change for agroforestry practice *i* in year t, metric tons CO_2

A_{it} = Land area under agroforestry practice *i* in year t, hectares

EF_i = emissions factor for agroforestry practice i, Mg C/ha/year

D_{1-5} = Discount factor for lagged years 1 to 5

$D_{\geq 6}$ = Discount percentage for lagged years 6 and beyond

$\frac{44}{12}$ = conversion factor from metric tons C to metric tons CO_2

The full set of calculations may be found in the Spreadsheet Appendix. Results from the five-year period of 2011 to 2016 are included here in Table T-25.

Table T-25: RESULTS – Omitted GHG flux estimate for agroforestry carbon stock change

	2011	2012	2013	2014	2015	2016
C stock change (MMT CO_2e)	-1.17	-1.37	-1.39	-1.58	-1.73	-1.91

Negative values indicate CO_2 sequestration.

ORCHARDS

The literature has suggested that net emissions from orchards are minimal, due to the removal of orchard trees at the end of their fruit-bearing lifetime (typically around 25-30 years). We have not found any additional evidence to improve upon this general belief, despite our own Tier 2 analysis to investigate otherwise. We sourced perennial crop acreage data from the USDA Agricultural Census and multiplied it by the IPCC-recommended factor for biomass accumulation rate in perennial above-ground woody biomass to calculate total net carbon flux. We accounted for the replacement of these perennials after reaching maximum productivity by subtracting from net carbon flux an estimate of orchard land area harvested and replaced, multiplied by the IPCC-recommended factor for biomass carbon loss rate of perennial above-ground woody biomass. This returned minimal net carbon emissions, which is in line with NGHGI statements regarding orchard carbon fluxes.

WOODLANDS

Although biomass and litter are also not accounted for in the grassland land category (with the exception of *Forests Converted to Grassland*), the NGHGI (2018) includes a preliminary estimate of grassland woody biomass for regions in the western U.S., which was found to be approximately 20 MMT CO_2 of sequestration. This estimate remained the same for 2017, as reported by the 2019 NGHGI. This pilot effort used the FIA database to estimate carbon stock changes and densities across 12 states in the western U.S., covering two FIA forest type groups, pinyon-juniper and woodland hardwoods. There are plans to expand this analysis and incorporate it in future inventories. Further note that forest to grassland conversion CO_2 estimates are discounted by about 50% in Western states, with the assumption that forests are being converted to woody savannah-grassland. It is not clear to what extent the 20 MMT CO_2 estimate overlaps with this 50% discount, but there is certainly woody-savannah grassland would not fall under forest to grassland conversion. Therefore the 20 MMT CO_2 estimate might be considered an upper bound of the woody savannah-grassland total omitted GHG flux.

LITTER

The NGHGI (2018) indicates that dead wood and litter carbon are insignificant in croplands and grasslands and are therefore not calculated as part of the NGHGI (outside of forest land conversions, in which dead wood and litter carbon stock changes are accounted for). The IPCC further notes that dead organic matter is an insignificant carbon flux except in agroforestry systems. In croplands, litter, like leaves or crop residue, can be incorporated into the soil through tillage and decomposition, thereby indirectly accounted for through soil organic carbon flux estimates, which are already closely accounted for in the NGHGI cropland and grassland sections. A literature search did not reveal any additional sources of data that would help estimate the carbon stock changes from dead organic matter in croplands and grasslands, and to date, the USDA does not appear to collect data relevant to this source. In grasslands, dead wood and litter are only considered in forest land conversions, though there is an initiative to calculate the omitted carbon stock change from woodlands. In summary, while there are consistent claims across authoritative sources that dead organic matter does not contribute significantly to carbon flux on croplands and grasslands, there also appears to be a dearth of data that to verify this claim.

BIOMASS AND LITTER RESULTS

In sum, omitted carbon sequestration from biomass and litter in croplands and grasslands is approximately 21.9 MMT CO_2e, after summing the carbon estimates for agroforestry and woodlands in 2016 (the most recent year of available data). This represents over 60% of the annual carbon stock change (34 MMT CO_2e) currently captured in cropland and grassland – a significant omission that, if included in the NGHGI, would increase the total carbon sequestration estimates across both land categories.

Non-CO2 emissions from combustion of woody biomass in grassland fires

The NGHGI quantifies CH_4 and N_2O emissions from grassland fires in the conterminous United States; however, the estimation by the NGHGI considers only the consumption of herbaceous biomass and does not consider consumption of any woody biomass existing on grasslands. We use a Tier 1 method from IPCC (2006) to estimate the CH_4 and N_2O emissions from the burning of woody biomass on grasslands in the conterminous United States. We apply the same emissions equation (Equation 3) from IPCC (2006) that we applied to estimate non-CO_2 emissions from both (1) forest fires (Section 2.2) and (2) herbaceous biomass combustion during grassland fires (Section 3.3).

The input parameters for the emissions calculation are shown in Table T-26. The NGHGI (2019) estimates that “land with perennial woody biomass” (we will refer to this below as “woodlands”) accounted for roughly 23.5 Mha in the conterminous United States and southeast and southcentral coastal Alaska in 2017. The NGHGI classifies this land area as either Grassland Remaining Grassland or Land Converted to Grassland.

Table T-26: Input parameters for the estimation of non-CO_2 emissions from woodland fires

Input parameter	Estimate
Burned area of woodlands	141,000 ha
Fuel consumption factor [a]	14.3 tons dry matter burned ha^{-1}
Emission factor (CH_4) [a]	2.3 g CH_4 emitted kg^{-1} [dry matter burned]
Emission factor (N_2O) [a]	0.21 g N_2O emitted kg^{-1} [dry matter burned]

(a) IPCC (2006).

We assume that 0.6% of woodland area is burned, based on the percentage of managed grassland area in the conterminous United States that was burned in 2014, which is the most recent year for which the NGHGI reports burned area estimates for grasslands. The percentage of grassland area burned for the conterminous United States is based on (1) the area of managed grassland burned in the conterminous United States in 2014 (1.659 Mha) reported by the NGHGI (2018) and (2) our estimate of the total area of managed grasslands in the conterminous United States for 2014 (275.3 Mha), which we calculated by subtracting the area of grassland in Alaska (50 Mha; NGHGI 2018) from the total area of managed grassland in all 50 states for 2014 (325.3 Mha; Table 6-6 of NGHGI 2018). Our estimate of total area of grassland in the conterminous United States in 2014 is a rough approximation since (1) it includes Hawai'I grassland and (2) the area of grassland in Alaska that is reported by the NGHGI only includes land belonging to the *Grassland Remaining Grassland* category and is not specific to individual years.

With reference to Equation 3, the fuel consumption factor in Table T-26 represents the product of the fuel availability and the combustion factor. We apply the fuel consumption factor for "all shrublands" from Table 2.4 of IPCC (2006). The CH_4 and N_2O emission factors are from Table 2.5 of IPCC (2006) and correspond to the combustion of "savanna and grassland." These emission factors are the same as those that are applied to estimate emissions from the combustion of herbaceous matter from grassland fires in Section 3.3. We apply the 100-year global warming potentials from IPCC (2007) to convert the CH_4 and N_2O emissions to a common scale: 25 kg CO_2e kg^{-1} [CH_4 emitted] and 298 kg CO_2e kg^{-1} [N_2O emitted].

The results of the omitted GHG flux estimation are shown in Table T-27. We estimate annual emissions of 4,637 tons CH_4 (0.12 MMT CO_2e) and 423 tons N_2O (0.13 MMT CO_2e) from woodland fires. We assume that these estimates account for the combustion of both woody biomass and herbaceous matter on these woodlands. To isolate the emissions from only woody biomass, we estimate the emissions from the combustion of herbaceous matter on the 141,000 ha of woodlands that are burned and subtract these emissions from the total woodland fire emissions.

To quantify emissions from the combustion of herbaceous matter, we use the same emission factors (2.3 g CH_4 emitted kg^{-1} [dry matter burned] and 0.21 g N_2O emitted kg^{-1} [dry matter burned]) and fuel availability (4.1 metric tons dry matter ha^{-1}) from IPCC (2006) as applied in Section 3.3. We follow the NGHGI in assuming that all available herbaceous matter is combusted (i.e., combustion factor = 1). We estimate that the combustion of herbaceous matter during woodland fires results in emissions of 1,330 tons CH_4 (0.03 MMT CO_2e) and 121 tons N_2O (0.04 MMT CO_2e). Thus, the combustion of woody biomass (net of herbaceous biomass emissions, which are already accounted for in Section 3.3) results in emissions of 3,307 tons CH_4 (0.09 MMT CO_2e) and 302 tons N_2O (0.09 MMT CO_2e).

Table T-27: RESULTS – Omitted GHG flux estimate for non-CO_2 emissions from woody biomass in grassland fires

Biomass type	Emitted CH_4 (metric tons CH_4)	Emitted CH_4 (MMT CO_2e)	Emitted N_2O (metric tons N_2O)	Emitted N_2O (MMT CO_2e)	CH_4 and N_2O (MMT CO_2e)
Woody biomass and herbaceous matter	4,637	0.12	423	0.13	0.25
Herbaceous matter	1,330	0.03	121	0.04	0.07
Woody biomass (Total)	3,307	0.09	302	0.09	0.18

Federal cropland and grassland

While most LULUCF GHG fluxes are estimated for federal land, there are some exceptions: soil C stock change in organic federal grassland soils, and indirect and direct N_2O emissions from federal croplands and grasslands with the exception of pasture/range/paddock (PRP) sources of N_2O. This section estimates the N_2O omitted fluxes by using existing EPA land representation data for 2016 (shared by NGHGI leads) and 2016 fluxes reported in the NGHGI (2018), to determine average N_2O emission factors for non-federal land. These emission factors are then applied to the federal land areas to calculate a first order estimate of the omitted fluxes. The following equation was used:

Equation 5: Emissions from federal croplands and grasslands

$$E_F = (\frac{E_L}{A_L}) * A_F$$

Where:

E_F = Emissions from omitted federal cropland/grassland flux

E_L = Emissions from equivalent non-federal cropland/grassland flux per the NGHGI

A_L = Area of non-federal land type

A_F = Area of omitted federal land type

We acknowledge that in reality, federal and non-federal lands are managed differently and would therefore have different emissions factors, this methodology is being used for purposes of first order approximation.

Note that we could not use this approach to estimate CO_2 emissions from organic soils in federal grasslands because we do not have data on the area of organic cropland/grassland soils on federal land. A very rough approximation, deriving organic soil C stock change over the entire non-federal cropland and grassland area, and assuming organic soil is present in equal proportions on federal and non-federal land, indicates this flux would likely be sizeable (2.8 MMT CO_2), but we don't include this value in our final results.

To estimate N_2O emissions from federal cropland, the total N_2O emissions from non-federal cropland (direct and indirect) was divided by total non-federal cropland area (including all *Land converted to Cropland*) and multiplied by the total federal cropland area (including all *Land converted to Cropland*).

To estimate omitted direct and indirect N_2O on federal grasslands, direct and PRP N_2O emissions and all indirect N_2O emissions from non-federal grasslands were subtracted from the total direct and indirect N_2O emissions on non-federal grasslands, since direct and indirect PRP N_2O is not omitted from federal land. Because indirect N_2O emissions are not reported by original source, we conservatively attributed all grassland indirect N_2O emissions to PRP manure. This net emissions total was divided by total non-federal grassland (including all *Land converted to Grassland*) and multiplied by the area of federal grassland (including all *Land converted to Grassland*). Note it was not necessary to subtract out PRP N_2O emissions from cropland because there is little grazing of cattle or other animals on cropland. These calculations can be found in the Spreadsheet Appendix.

In sum, it is estimated that the current NGHGI omits 21.76 MMT CO_2e from federal lands, a sizeable value. This is nearly 10% of the total N_2O from U.S. croplands and grasslands as reported for 2016 (NGHGI 2018).

Additional uncertainty on federal lands includes lack of specificity of crop type and input intensity, which we did not attempt to quantify here.

Soil microbial methane sink

The NGHGI accounts for methane fluxes associated with rice production, fires, wetlands, and drained organic soils. Mineral soils are also responsible for a significant methane sink – driven by methanogens – that is not currently considered in the NGHGI, and possibly for good reason. It is not clear how much of the microbial methane sink can be attributed to anthropogenic management. Furthermore, the soil methane sink is directly tied to the atmospheric lifetime of methane, and is likely already considered to some extent in the calculation of methane global warming potential (GWP). However, for purposes of NGHGI accounting, it is useful to have an understanding of all sources and sinks and therefore data to estimate this sink at the national level has value. If countries decide to estimate the soil methane sink via GHG inventories, there will need to be a process to decide to account for its contribution to methane GWP as well as any methane mitigation efforts.

To calculate this omitted GHG flux, we multiply the total estimated area of cropland, grassland and forest mineral soils in the U.S. by emissions factors identified in the literature. We included forests in this analysis because the literature suggests they account for a significant part of the soil methane sink which was important to consider when fully assessing CH_4 fluxes from soils.

From the total respective area of these three land types, we subtracted out the area for Alaska since the state is largely unaccounted for in the 2018 NGHGI. To account for the removal of organic and wet soils, which tend to have limited methane oxidation due to their high soil water content, the percentage of soil comprised by mineral soil was found by dividing the mineral soil area of each land type into the total land area. Then, these mineral soil percentages were multiplied by the land area, not including Alaska. For grassland and cropland, this land area was then multiplied by the CH_4 uptake rates by land type as noted in Dutar and Verchot (2007), a meta-analysis of 120 studies that reported CH_4 fluxes from different terrestrial biomes: 2.32 kg CH_4 ha^{-1} yr^{-1} for grasslands, and 1.23 kg CH_4 ha^{-1} yr^{-1} for croplands. These CH_4 fluxes were similar to those noted in an earlier paper authored by one of the NGHGI soil leads: 2 kg CH_4 ha^{-1} yr^{-1} for grasslands and 1 kg CH_4 ha^{-1} yr^{-1} for croplands (DelGrosso et al. 2000).

The literature suggests that methane uptake rates are consistently higher in forests compared to all other ecosystems, and soil texture (coarse, medium, and fine) is of particular importance in temperate forests

(DelGrosso et al. 2000; Dutar and Verchot 2007). Given this distinction, forests were treated with greater granularity. Using data from the FIA and SSURGO, it was determined that U.S. forests are comprised of 21% clay soil, 35% silt, and 44% sand. These soil textures were used as proxies for the soil textures used in the literature (clay = coarse; silt = medium; sand = fine). The soil land area without Alaska was then multiplied by each of these percentages to estimate the breakdown of forest soils by the three soil textures. Then, using uptake factors found in Dutar and Verchot (2007) , each soil texture was multiplied by its respective CH_4 uptake rate (7.5 kg CH_4 ha^{-1} yr^{-1} for coarse soils, 5.5 kg CH_4 ha^{-1} yr^{-1} for medium soil, and 2.6 kg CH_4 ha^{-1} yr^{-1} for fine soils) to estimate total CH_4 uptake rate by U.S. forest soils.

The combined soil methane sink is 25.12 MMT CO_2e (14.67 MMT CO_2e for grassland, 6.64 MMT CO_2e for cropland, and 3.81 MMT CO_2e for forests).

Table T-28: RESULTS – Omitted GHG flux estimate for soil microbial methane sink

Land type	Area of mineral soil (ha)	CH_4 flux factor (CH_4 ha^{-1} yr^{-1})	Total MMT CO_2e
Grassland	189,687,098	2.3	14.7
Cropland	161,831,536	1.2	6.6
Forest – coarse	5,173,808	7.5	1.3
Forest – medium	8,623,013	5.5	1.6
Forest - fine	10,840,359	2.6	0.9
Total			**25.1**

4 Settlements

4.1 Carbon stock change in urban trees

NGHGI METHODS

Carbon stock change in urban trees is the primary driver of GHG fluxes from Settlements, as reported in the NGHGI (2018). This estimate is calculated for each state using a combination of state-level and nationally averaged values.

Determining the amount of land classified as "settlement" is a necessary but challenging component of calculating the carbon flux from urban trees. The National Resources Inventory (NRI) provides an estimate of settlement area, but because this dataset has not been updated since 2012 as of the 2018 NGHGI, settlement area from National Land Cover Database (NLCD) is utilized for Inventory years since 2012. For the 2018 NGHGI and for the estimation described here, classifications of urban area, as defined by population density from the US Census Bureau, were used as a proxy for settlement area, although it has been identified as an underestimate of overall settlement area compared to the NGHGI land representation estimates. Starting in the 2019 NGHGI, however, settled area was determined using both satellite images of tree cover and the NLCD, more closely matching the method for determining national land cover as other components of the Inventory and providing a much closer estimate to settlement land area determined by NRI, as outlined in Table T-29. This change in method has increased the overall urban tree sequestration estimate by approximately 33% given the higher land area classified as settlement.

Table T-29: Comparison of settlement land area classifications (NGHGI 2018)

Land area definition	Settlement	Developed	Urban
Source	National Resources Inventory (NRI) 2011	National Land Cover Dataset (NLCD) 2011	US Census based on population area 2010
Inventory Year(s) Used	Land Representation, all Inventory years	2019 Publication year	2018 Publication year and before
Hectares	42,519,645	45,411,098	27,347,901

Once settlement area is estimated, state-level average urban tree cover percentages are derived. For the 2018 NGHGI and previous inventories, values were taken from Nowak and Greenfield (2013) for each state, combining the values designated as "Urban" and "Community" areas in table 1 of Nowak and Greenfield (2013). For the 2019 NGHGI and moving forward, NLCD is used to estimate settlement area by aggregating NLCD classifications of "open space", "low intensity", "medium intensity", and "high intensity" by state. These sum to TC_s^{NLCD} in Equation 6. Because NLCD has been demonstrated to underestimate tree cover (Nowak and Greenfield 2010), photo interpretation of tree cover was completed for the years 2011 and 2016 to determine national values for urban tree cover, expressed in percentages. These were then applied to state-level values to scale up state-level NLCD estimates of urban tree cover percentages.

Equation 6: Percent urban tree cover by state (NGHGI 2018)

$$TC_s = TC_s^{NLCD} * \frac{TC_N^{Photo}}{TC_N^{NLCD}}$$

Where:

TC_s = Percent urban tree cover in state *s* used in NGHGI calculations

TC_s^{NLCD}= Percent urban tree cover in state *s* as determined by the NLCD

TC_N^{Photo}= National percent tree cover in urban areas using photo-interpretation

TC_N^{NLCD} = National percent tree cover in urban areas as determined by the NLCD

State-level estimates of urban tree cover area, estimated by multiplying settlement land area by percent tree cover, are then multiplied by a gross sequestration value, taken primarily from Nowak (2013). Gross sequestration values are derived from sample plots in several U.S. cities using the i-Tree model (Nowak et al. 2008), which estimates both carbon storage and sequestration rates. These gross sequestration rates vary from 0.168 kg C/m^2 cover/year (Alaska) to 0.581 kg C/m^2 cover/year (Hawaii) based on tree species mix, tree density, and climatic factors.

To determine the net sequestration ratio, defined as gross sequestration adjusted for tree removal and death, a net to gross sequestration ratio is applied for each state. The national average ratio, 0.74, is taken from Nowak et al. (2013) and applied to each state unless a state-specific value is available (North Dakota, South Dakota, Nebraska, Indiana, Tennessee, Kansas, and Washington DC have state-specific values).

The full equation for the changes in stock status for urban trees is outlined below (Equation 7). The full set of calculations may be found in the Spreadsheet Appendix.

Equation 7: Carbon stock change in urban trees (NGHGI 2018)

$$\Delta CO_{2_t} = 1{,}000 * \frac{44}{12} * \sum_{s=1}^{S} A_{st} * TC_s * GS_s * GN_s$$

Where:

ΔCO_{2_t} = Total carbon stock change for urban trees in year *t*, metric tons CO_2

s = 1,…,S, representing each state

A_{st} = Urban area in state *s* in year *t*, square kilometers

TC_S = Percent urban tree cover in state *s*

GS_S = Gross sequestration rate in in urban trees in state *s*, kg C/m^2 cover/year

GN_S = Gross to net sequestration ratio in urban trees in state *s*

PROJECT METHODS

In order to determine the contribution to uncertainty of each variable in Equation 7, we ran a contribution index analysis consistent with Ogle et al. (2003) using Equation 1 above. To complete this analysis, the standard error of each of the Equation 7 parameters (urban area, percent tree cover, gross sequestration rate, and gross to net sequestration ratio) were determined from the literature or the NGHGI (2018). Table T-30 below identifies the source for each uncertainty parameter. Consistent with Ogle et al. (2003) method, each parameter's uncertainty estimation was set to zero, and the new uncertainty for urban trees was calculated. The total error of the urban trees calculation is calculated by taking the square root of the sum of each parameters' square. Relative contribution of each parameter to uncertainty was estimated by determining the difference in uncertainty between each parameter's zeroed out value and the total uncertainty for the calculation. The percentage of these differences relative to the total uncertainty is that parameter's relative contribution to uncertainty; the sum of these percentages comes to 100%.

Table T-30: Uncertainty parameters and sources for urban trees

Parameter	Standard Error	Source
Urban Area	+/- 10%	Expert judgment, NGHGI 2018
Tree Cover Percentage	Varies by state; see Spreadsheet Appendix for full list	Nowak and Greenfield 2012, Table 1
Gross Sequestration Rate	+/- 16.2%	Nowak et al. 2013
Gross to Net Ratio	+/- 50.5%	Nowak et al. 2013

RESULTS

The results of the contribution index analysis show that the gross to net sequestration ratio accounted for the largest portion (83%) of urban tree uncertainty (Table T-31), with urban area estimation and state-wide sequestration rate both accounting for 6-7% of uncertainty.

Table T-31: RESULTS – Contributions to uncertainty of urban tree carbon stock change

Variable held constant	Range of 95% Interval (MMT CO_2e)	Contribution to Uncertainty (%)	Contribution to Uncertainty (MMT CO_2e)
None (all vary)	104.3	–	–
Urban Area	100.1	6.2	6.5
Tree Cover Percentage	101.5	4.1	4.3
Gross Sequestration Rate	99.7	6.7	7.0
Gross to Net Ratio	48.0	83.0	86.5

DISCUSSION

The 95% confidence interval we found for urban trees (-145.0 to -40.7 MMT CO_2) generally matches that reported in the 2018 NGHGI for 2016 (-136.9 to -47.9 MMT CO_2), and we calculate the exact same mean (-92.9 MMT CO_2), providing confidence in our calculation methods.

The gross to net sequestration ratio for urban trees contributes significantly not only to the uncertainty of the estimation of urban trees, but for settlements and the LULUCF GHG inventory as a whole. This national average, taken from Nowak et al. (2013), is applied across the majority of states because no state-levels factors are available. Additional research could be completed to decrease the uncertainty in this factor for state-level estimates if the current method of estimating urban trees is used in future inventories.

For future inventories, the methods used to estimate urban trees could be further harmonized with those methods used in the forestry section. Methods for estimating biomass from the i-Tree method are consistent with using the Jenkins et al. (2003) (used in the LULUCF forestry section). However, as made clear by this analysis, the gross to net ratio is by far the largest source of uncertainty, and the use of this ratio could be avoided if the same carbon estimation methods were used across forests and urban trees.

4.2 Carbon stock change in yard trimmings and food scraps

NGHGI METHODS

Biological waste disposed in landfills, including food scraps and yard trimmings, stores carbon and emits CH_4 and CO_2 through decay. The net carbon stock change from yard trimmings and food scraps is a function of the quantity of biological material decomposed in a landfill and the physical characteristics of the waste, including moisture and carbon content. To quantify annual carbon stock change in yard trimmings and food scraps, the NGHGI (2018) calculates the difference between carbon stocks in year *t* and year *t-1*.

The first step is to determine the volume of biological material in U.S. landfills. The NGHGI time series for biological materials entering landfills goes back to 1960. The initial waste volume of each of the waste components is determined from the EPA guidance document, Advancing Sustainable Materials Management: Facts and Figures 2014 (ASMM 2014). Linear interpolation of historical data between 1960-2000 is computed. The years 2015 and 2016 are assumed to have the same volume as 2014. The amount of composted material, taken from ASMM 2014, is removed from the estimate of waste, and the percent of municipal solid waste (MSW) is multiplied by the volume of each material reaching the landfill. Finally, for yard trimmings, the proportion of each material is multiplied by the total yard trimmings volume to determine the volume for grass, leaves, and branches (Table T-32).

Table T-32: Proportion of yard trimmings (ASMM 2014)

Material	Percentage of total yard trimmings (%)
Grass	30.3
Leaves	40.1
Branches	29.6

Next, the carbon content of the dry material is estimated. The wet tonnage of the material is converted to dry weight using values from Tchobanoglous et al. (1993). This value is then multiplied by the percentage of dry material that is carbon, taken from Barlaz (1998, 2005, 2008). Both percent moisture content and initial carbon content are outlined in Table T-33 below.

Table T-33: Yard trimmings moisture and initial carbon content (Barlaz 1998, 2005, 2008)

Material	Percentage Moisture Content (%)	Initial Carbon Content (%)	Carbon Storage Factor (%)	Decay Rate (k)
Food Scraps	70	50.8	15.7	0.156
Grass	70	44.9	53.5	0.323
Leaves	31	45.5	84.6	0.185
Branches	10	49.4	76.9	0.016

For each year beginning in 1960 and applied through to the most recent Inventory year, the decay of each year's waste is estimated using Equation 8 and with additional parameters of carbon storage factor and decay rate outlined in Table T-33. The total carbon stock is the sum of all previous years' stocks adjusted for decay over time. For example, for the 2014 inventory year, the total carbon stock is equal to the undecayed carbon stock from biological waste deposited every year from 1960-2014 (inclusive).

Equation 8: Landfilled yard trimmings and food scrap carbon stock (NGHGI 2018)

$$LFC_{i,t} = \sum_{s=0}^{t} W_{i,s} * (1 - MC_i) * \{[CS_i * ICC_i] + [(1 - (CS_i * ICC_i)) * e^{-k(t-s)}]\}$$

Where:

- t = Year for which C stocks are being determined
- i = Waste type for which C stocks are being estimated (grass, branches, leaves, or food scraps)
- $LFC_{i,t}$ = stock of C in landfills in year t, for waste i (metric tons)
- $W_{i,s}$ = Mass of waste i disposed of in year s (metric tons, wet)
- s = 0,…,t; Year in which waste is disposed of
- MC_i = Moisture content of waste
- CS_i = Proportion of C stored for waste
- ICC_i = Initial C content of waste
- k = First order decay rate for waste i

PROJECT METHODS

A Monte Carlo simulation of 10,000 runs was completed to determine the relative contribution to uncertainty for each of the parameters identified above using Equation 1 above (Ogle et al. 2003). All of the parameters were assumed to be normally distributed except for percentage carbon stored, which was assumed to be uniformly distributed, and the decay rates, which have triangular distributions. Parameters within a set (e.g., all the values for the 'fraction of total weight' parameter) were bounded to sum to 100% when added together and to be individually bounded between 0-100%. All of the parameters were held to bounds as determined by ICF International (2007) except for the decay rates, which are consistent with values in De la Cruz and Barlaz (2010). The assumed standard error for each parameter can be found in the Spreadsheet Appendix. The contribution index formulation allows for negative contributions to uncertainty, and we find that the decay rates have a contribution to uncertainty of -3.8%. This could be due to covariance with another element. We therefore scaled the percentage contributions so that the sum of their absolute values is 100%. The result is that the sum of the contributions to uncertainty in MMT CO_2e over all of the uncertainty elements is equal to the range of the 95% confidence interval derived from the Monte Carlo simulation where all variables are allowed to vary.

RESULTS

Mean values and variance were calculated using the output of the Monte Carlo simulations and the fluxes were summed to include all four components of yard trimmings and food scraps. The results summarized in Table T-34 show that the largest contributors to Yard Trimmings and Food Scraps uncertainty are the food scraps multiplier (40.9%) and the percentage of carbon stored (24.9%).

Table T-34: RESULTS – Contribution to uncertainty of yard trimmings and food scraps carbon stock change

Variable held constant	Range of 95% confidence interval (MMT CO_2e)	Contribution to Uncertainty (scaled, %)	Contribution to uncertainty (MMT CO_2e)
None (all vary)	14.3	–	
Food Scraps Multiplier	11.0	40.9	5.8
Percent Carbon Stored	12.3	24.9	3.6
Moisture Content	13.4	11.4	1.6
Yard Trimmings Multiplier	13.5	10.2	1.5
Initial Carbon Content	13.9	5.1	0.7
Fraction of Total Weight	14.0	4.0	0.6
Decay Rates	14.6	3.5	0.5

DISCUSSION

Our calculation methods generally reproduce the mean flux value reported in the NGHGI (2018) for yard trimmings and food scraps, with our methods estimating -10.8 MMT CO_2 and the NGHGI (2018) reporting -12.1 MMT CO_2. Our Monte Carlo methods also capture a similar 95% confidence interval, with our methods estimating -17.9 to -3.6 MMT CO_2 and the NGHGI (2018) reporting -19.0 to -4.8 MMT CO_2, with all negative values representing CO_2 sequestration.

The yard trimmings and food scraps is not a significant area of uncertainty in the overall LULUCF inventory, but the multiplier values used to disaggregate yard trimmings and food scraps volume into different categories of biological waste (food scraps, grasses, leaves, branches) account for combined more than half of the uncertainty in this section. These values are not currently updated over time, despite likely changes. Additional research into the yard trimmings and food scraps multipliers could significantly reduce the uncertainty from this category, should that be of interest.

4.3 N_2O from settlement soils

Direct and indirect emissions from N additions to settlement soils comprised 7 MMT CO_2e in 2016 and were calculated using Tier 1 methodology (NGHGI 2018). Direct N_2O emissions from settlement soils stem from biosolids (e.g., sewage sludge), synthetic N fertilizers applied to lawns, golf courses, and other landscaping; and enhanced mineralization of N in drained organic soils. Indirect emissions come from N additions that are converted to a form other than N_2O, and then later converted to N_2O at an off-site location.

For direct N_2O emissions from synthetic fertilizers, N additions are estimated using 1990-2012 USGS on-farm and non-farm fertilizer use estimates, which is based on fertilizer sale data. This amount is then multiplied by the IPCC default emission factor of 1% for converting applied N to N resulting in direct N_2O emissions. For direct N_2O emissions from biosolids, biosolid application estimates are calculated from national data on biosolid generation, disposition, and N content, and then multiplied by the same IPCC factor. For drained organic soil, the total area of drained organic soils is calculated using the 2012 NRI and SSURGO, then multiplied by the IPCC default emission factor for temperate regions. This estimate does not currently include Alaska or federal lands (see the discussion on Federal cropland and grassland omitted GHG flux above).

To estimate indirect emissions, the IPCC default factors for volatilization (10%) and leaching and runoff (30%) is multiplied by the total N applied from fertilizer and sludge, respectively. These numbers are then multiplied by the IPCC default factor of 1% for portion of volatilized N converted to N_2O off-site, or the IPCC default factor of 0.75% for the portion of leached and runoff N that is converted to N_2O off-site. For both direct and indirect N_2O emissions, a surrogate data method is used to calculate estimates from 2013 to 2016.

Uncertainty is estimated through a Monte Carlo analysis, and combined with the uncertainty from biosolids application using error propagation methods. Uncertainty stems from several sources: N inputs, variables that influence rate of nitrification and denitrification, fertilizer N and biosolid application rates, variance in the NRI data, and IPCC default factors. It also comes from the surrogate data method used to estimate the time series from to 2013-2016.

Due to the small contribution of N_2O fluxes from N additions to settlement soils (Table T-35), we did not perform uncertainty attribution analysis beyond what is reported in the NGHGI (2018).

Table T-35: RESULTS – Contributions to uncertainty of N_2O emissions from settlement soils

Variable held constant	Range of 95% confidence interval (MMT CO_2e)	Contribution to uncertainty (%)	Contribution to uncertainty (MMT CO_2e)
None (all vary)	1.3	–	–
Direct N_2O Fluxes	0.3	97.0	1.3
Indirect N_2O Fluxes	1.3	3.0	0.0

4.4 Carbon stock change in drained organic settlement soils

Similar to drained organic soil emissions from croplands, estimates of CO_2 emissions from drained organic soils in settlements (1.3 MMT CO_2e) follow a Tier 2 methodology and use the U.S.-specific emissions factors for cropland because settlement organic soils are assumed to have similar CO_2 emissions rates as croplands (NGHGI 2018). Settlement organic soil area, calculated from the NLCD and the 2012 NRI, is multiplied by IPCC default emission factors to estimate net carbon stock change. Uncertainty is estimated through a Monte Carlo analysis. Emissions from 2013 to 2016 are estimated using a linear extrapolation because the NRI activity data was not available for those years in the 2018 NGHGI, which contributes to additional uncertainty.

Due to the small contribution of CO_2 fluxes from drained organic soils (Table T-36), we did not perform uncertainty attribution analysis beyond what is reported in the NGHGI (2018).

Table T-36: RESULTS – Contribution to uncertainty for drained organic settlement soils

Variable held constant	Range of 95% confidence interval (MMT CO_2e)	Contribution to uncertainty (%)	Contribution to uncertainty (MMT CO_2e)
Drained organic settlement soil	1.0	–	1.0

4.5 Omitted GHG flux – Carbon stock change in settlement mineral soils

NGHGI METHODS

The NGHGI does not include an estimation of GHG fluxes from mineral soils in *Settlements Remaining Settlements,* despite the fact that mineral soils in the US account for more than 99.75% of the land area of soils in the country, and a similar ratio is likely to hold for settlement areas. Omitting carbon stock changes in settlement mineral soils is consistent with IPCC (2006) guidance. While the NGHGI (2018) estimates mineral soil fluxes for *Land Converted to Settlements*, the current inventory does not account for mineral soil fluxes from *Settlements Remaining Settlements*, citing a lack of activity data.

PROJECT METHODS

IPCC guidance indicates there is insufficient data for developing emissions factors for settlement mineral soil Tier 1 or 2 estimation. We use methods consistent with IPCC (2006) guidance and Tier 2 factors (NGHGI 2018, Table A-215) for cropland mineral soils, with input parameters summarized in Table T-37. Reference carbon stocks was taken from low clay activity mineral soils in cold temperate, dry climates and management stock change factor of 0.9 was used, consistent with low input cropland. Other default values for Tier 2 calculations were used, consistent with Tier 2 methods to calculate a per-hectare emissions factor of 0.825 MT CO_2e. The total urban land area taken from the urban trees calculation was multiplied by this emissions factor to estimate an emissions value from mineral soils on urban land.

Table T-37: Input parameters for Tier 2 urban mineral soil GHG flux

	Units	Value	Consistent With
Reference carbon stock	Tons C ha^{-1}	45	Low clay activity mineral soils
Stock change value for land-use system	Dimensionless	1	Assuming settlement remaining settlement
Stock change factor for management regime	Dimensionless	0.9	Low input cropland
Stock change factor for input of organic matter	Dimensionless	1	Assuming no change in organic matter inputs
Time change factor for stock change	Years	20	Default value in Tier 1/2 calculations
Settlement land area	Million hectares	43	Total Settlement area (NGHGI 2018, Table 6-6)

RESULTS

Using equation 2.25 from IPCC (2006) guidance and input parameters from Table T-37, we estimate an annual emission of 34.7 MMT CO_2, roughly the same amount as those coming from total croplands and grasslands.

DISCUSSION

The size of emissions from mineral soils on urban land was much higher than we expected, calculated as roughly the same as those found on croplands and grasslands. One challenge is that we were not able to remove impervious surfaces from urban land area. Even controlling for this, the emissions estimate is sizeable, considering the smaller settlement area compared to cropland and grassland.

This estimate is relatively high, and not especially satisfying given that low input cropland is not well-aligned with management practices on settlement soils. However, a recent study by Decina et al. (2016) estimates that fluxes from urban soils in Boston are as much as 2.62 times higher than those on nearby soils, while also noting significant differences between land use types such as lawn and forests. Emissions estimates generated from the emissions factors in that paper produce results significantly higher than those estimated here, suggesting that urban soils may indeed be a significant source of emissions. Further research and data are needed to estimate emissions from urban mineral soils across the country, such as additional measurements taken on urban soils beyond Boston.

5 Wetlands

The NGHGI (2018) defines wetlands as areas where the water table is artificially changed or created through human activity that do not fall into Forest, Cropland, or Grassland categories, consistent with IPCC guidance (IPCC 2014). Therefore the NGHGI (2018) focuses exclusively on coastal wetlands, the only wetlands category unlikely to overlap with other land use categories, along with managed peatlands. All coastal wetlands are included in the NGHGI, without regard for managed vs. unmanaged designation due to lack of data. By only focusing on coastal wetlands (comprising approximately 2.9 million hectares), there are over 40 million hectares of wetlands not accounted for in the NGHGI, including about 13 million hectares of inland and coastal wetlands in Alaska and Hawaii, with the remainder comprised of inland wetlands in the contiguous United States.

A large challenge with U.S. wetlands is that there is a lack of data to determine which wetlands are managed vs. unmanaged, particularly for inland wetlands. No datasets currently allow for making this determination in the United States. Due to the lack of data, we do not attempt to quantify this omission in the NGHGI, however it could be sizeable given that the omitted area is approximately four percent of the managed U.S. land base.

5.1 CO_2, N_2O, and CH_4 from managed peatlands

Managed peatland GHG emissions are apportioned into off-site CO_2 emissions and on-site CO_2, N_2O, and CH_4 emissions. On-site emissions occur due to land clearing and exposing the underlying peat to oxygen, which results in CO_2 formation. Draining these landscapes also results in on-site N_2O and CH_4 production. Off-site emissions occur due to dissolved organic carbon draining from managed peatlands and reacting with other compounds to form CO_2. Most (94%) managed peatland emissions occur offsite.

Offsite CO_2 emissions are calculated by converting annual weight of U.S. peat production, both in the lower 48 states and Alaska, into estimates of managed peatland area using an average per hectare peat production rate derived from U.S. and Canadian data. These estimates are stratified by nutrient-rich vs. nutrient poor peat deposits. Peat production area estimates and then multiplied by IPCC default C conversion factors (IPCC 2006). Peat production statistics come from USGS and Alaska Department of Natural Resources official reports (USGS 1991-2016, 2018; DGGS 1993-2015). Alaska peat production is recorded in volume, so these values must be converted to weight to be consistent with lower 48 estimates. The NGHGI does not include off-site CO_2 emissions from peat produced outside the United States.

Onsite emissions include CO_2, N_2O, and CH_4 estimates. Peat production area estimates, as derived above, are multiplied by IPCC default emissions factors for CO_2 and CH_4 (IPCC 2006, 2014). Additional CH_4 is also emitted from drainage ditches, the area of which are estimated using the IPCC default fraction of peatland area containing drainage ditches and then multiplied by the IPCC default emissions factor (IPCC 2014).

The NGHGI estimates uncertainty of off-site and on-site peat emissions using a Monte Carlo analysis that accounts for uncertainty related to (with standard deviation as a percentage of mean listed):

- Peat production data, ±25%
- Percent type of peat production (nutrient-rich vs. nutrient poor), ±25%
- Bulk density of lower 48 and Alaska peat, ±25%
- IPCC default emissions factors, C fraction factor, fraction of peatland covered by ditches, IPCC default uncertainty (2006, 2014)

Note that uncertainty due to conversion of production tonnage to area of managed peatland is not accounted for. Identifying more data to calculate this factor or derive peatland area directly is noted as an NGHGI planned improvement. The current source for Alaska peat production data may be discontinued and only includes responses from half of Alaskan peat producers, so better data is needed here.

Due to the small contribution of GHG fluxes from peatlands (Table T-38), we did not perform uncertainty attribution analysis beyond what is reported in the NGHGI (2018).

Table T-38: RESULTS – Contributions to uncertainty of managed peatland CO_2, N_2O, CH_4 emissions

Variable held constant	Range of 95% confidence interval (MMT CO_2e)	Contribution to uncertainty (%)	Contribution to uncertainty (MMT CO_2e)
None (all vary)	0.2	–	–
Offsite, Onsite – CO_2	0.2	100	0.2
Onsite – N_2O	–	–	–
Onsite – CH_4	–	–	–

Note that onsite N_2O and CH_4 fluxes and uncertainty ranges do not exceed 0.05 MMT CO_2e, and so contribute negligibly to total uncertainty of peatland emissions.

We do not attempt to quantify potential omitted fluxes from peatland, such as new land cleared for peat extraction or offsite non-CO_2 emissions, because U.S. peatland emissions have been declining steadily since 1990 and any omissions would likely be insignificant.

5.2 Carbon stock change and CH_4 in coastal wetlands

Coastal wetlands are defined as wetlands found below the elevation of high tides and extending as far seaward as intertidal vascular plants can be found, including both federal and non-federal lands.
The NGHGI coastal wetlands section includes:

- Carbon stock changes and CH_4 emissions from vegetated coastal wetlands remaining vegetated coastal wetlands;
- Carbon stock changes on vegetated coastal wetlands converted to unvegetated open water coastal wetlands and vice versa; and
- N_2O emissions from aquaculture in coastal wetlands.

Coastal wetland area is estimated and stratified using the National Oceanographic and Atmospheric Administration (NOAA) Coastal Change Analysis Program (C-CAP), which is not harmonized with other land area representation datasets used in the NGHGI (2018), including National Resources Inventory

(NRI), Forest Inventory and Analysis (FIA), and National Land Cover Database (NLCD). C-CAP is updated every four to five years, with the most recent dataset updated in 2010. Coastal wetland areas and land use change is extrapolated from 2010 to the latest NGHGI inventory year using past C-CAP land areas and assuming continuing trends.

Carbon stock change estimates cover aboveground biomass and soil carbon, omitting estimates of belowground biomass, dead organic matter, and litter due to lack of data. Note that aboveground biomass was included for the first time in the 2019 NGHGI.

Soil carbon stock changes are estimated equivalently for mineral and organic soils using U.S.-specific emissions factors derived from the literature, stratified by climate zone and wetland type (freshwater vs. saline, and further subdivided by emergent marsh, scrub shrub, and forested). Each emissions factor is multiplied by land area of its respective climate/wetland type. For vegetated to unvegetated conversions and vice versa, soil disturbance of 1 meter is assumed. All emissions are assumed to occur in the year of conversion. Note that there is no discussion in the NGHGI wetlands sections of soil carbon stock change estimation consistency across land types, which will create inconsistent estimates of soil carbon fluxes for land use change to and from coastal wetlands.

Aboveground biomass is estimated using a national assessment combining plot and remote sensing data (Byrd et al. 2017, 2018).

Soil CH_4 emissions are estimated using Tier 1 methods, multiplying coastal wetland area by IPCC default CH_4 factors, stratified by wetland type. For vegetated to unvegetated conversions and vice versa, a Tier 1 assumption is applied such that methane emissions are zero due to unchanged salinity conditions.

N_2O from aquaculture in coastal wetlands is estimated using Tier 1 methods, multiplying U.S. seafood production by IPCC default emissions factors (IPCC 2014). All aquaculture production of catfish, striped bass, tilapia, trout, crawfish, salmon, and shrimp are included in these estimates.

There is also a NGHGI (2018) section for *Land converted to Wetlands*, referring to non-wetland conversions to wetland, but which only covers land converted to vegetated coastal wetland. This section covers soil carbon stock change, aboveground biomass carbon stock change, and soil CH_4 emissions. It does not appear that this section accounts for carbon stocks on the original land use type, though land conversion to wetland occurs across all land use types, including forests. This could be a significant omission, in proportion to the scale of wetland emissions, which are small.

Due to the small contribution of each category of coastal wetlands GHG fluxes (Table T-39), we did not perform uncertainty attribution analysis beyond what is reported in the NGHGI (2018) for the four categories described above (aboveground biomass carbon stock change, soil carbon stock change, soil CH_4 emissions, N_2O from aquaculture). In Table T-39 we combine these four categories across vegetated coastal wetland remaining coastal wetland and all land use changes.

Table T-39: RESULTS – Contributions to uncertainty of coastal wetlands CO_2 and CH_4 emissions

Variable held constant	Range of 95% confidence interval (MMT CO_2e)	Contribution to uncertainty (%)	Contribution to uncertainty (MMT CO_2e)
None (all vary)	4.5	–	–
Soil C stock change	2.2	77.7	3.5
Aboveground biomass C stock change	4.5	0.0	0.0
Soil CH_4	3.9	21.9	1.0
N_2O from aquaculture on coastal wetlands	4.5	0.4	0.0

6 Alaska, Hawaii, and Territories

The NGHGI does not cover all GHG flux categories in Alaska, Hawaii, and U.S. territories (including Puerto Rico, U.S. Virgin Islands, Guam, Northern Marianas Islands, and American Samoa). Table T-40 shows that there is no LULUCF NGHGI data for U.S. Territories (comprising 0.1% of U.S. land base, Table T-41). Alaska is missing coverage for most land use and agricultural categories except forests. Hawaii's forest carbon and wetland fluxes are not included, but cropland, grassland, and settlement GHG fluxes generally are. The NGHGI first started recording forest GHG fluxes in interior Alaska in the 2019 publication, now covering all managed Alaskan forest land (over 30 million hectares, or 11% of total managed U.S. forest area). The NGHGI notes in many sections of the report that expanding coverage outside the conterminous United States (CONUS) is a planned improvement.

Table T-40: NGHGI categories included for Alaska, Hawaii, and U.S. Territories for 2018 and 2019 NGHGI publication years

NGHGI Category	Sub-category	NGHGI Publication Year					
		Alaska		Hawaii		Territories	
		2018	2019	2018	2019	2018	2019
Ag. soil mgmt.	N_2O, mineral and PRP N	✓	✓	✓	✓		
Ag. soil mgmt.	N_2O, other N additions[a]						
Ag. soil mgmt.	N_2O, drained organic soils			✓	✓		
Rice methane		N/A	N/A	N/A	N/A		
Forests	C stock change[b]	Coastal only	✓				
Forests	N_2O, N additions[c]	N/A	N/A	N/A	N/A		
Forests	N_2O, drained organic soils[c]	N/A	N/A	N/A	N/A		
Forests	Non-CO_2, forest fires	✓	✓				
Cropland	Soil C stock change			✓	✓		
Grassland	Soil C stock change			✓	✓		
Grassland	Non-CO_2, grassland fires			✓	✓		
Wetlands	Peatlands[d]	✓	✓	N/A	N/A		
Wetlands	C stock change						
Wetlands	N_2O, aquaculture[e]	✓	✓	✓	✓		
Settlements	Drained organic soils, C			✓	✓		
Settlements	Urban trees	✓	✓	✓	✓		
Settlements	N_2O, drained organic soils			✓	✓		
Settlements	Yard trimmings, food scraps[e]	✓	✓	✓	✓		

NGHGI Categories listed here include both, for example, cropland remaining cropland and land converted to cropland calculations. (a) Includes manure, residues, biosolids, sludge, and other organic fertilizers; (b) Forest carbon stock change does not include estimates of land converted to forest in Alaska for either 2018 or 2019; (c) NGHGI 2019 includes forested areas with known N application, southeastern CONUS and western Oregon and Washington; only 8 states have known artificially regenerated forest on organic soil based on all NFI annual plots, a proxy for drained organic soil, and this is not found in Alaska or Hawaii; (d) Alaska data is included although the data source has been unreliable and must be updated; (e) It is not clear whether Hawaii and Alaska are included in these categories although it appears that they would be due to data included in USDA Census of Aquaculture (2013) and Advancing Sustainable Materials Management: Facts and Figures 2015 (EPA 2018).

Table T-41: Land area (hectares) in Alaska, Hawaii, U.S. Territories by land use type, managed land only

	Alaska	Hawaii[d]	Territories[e]
Forests	30,700,000[a]	797,106	482,962
Cropland	28,700[b]	95,117	20,764
Grassland	50,000,000[c]	1,279,565	342,777
Wetlands	12,927,525[d]	9,765	31,252
Settlement	180,105[d]	243,399	154,496
Other	23,853,885[d]	406,147	13,133
Total	171,800,000	2,831,100	1,045,385

(a) NGHGI 2018 estimate of south central and southeastern coastal Alaska managed forest land plus NGHGI 2019 estimate of interior Alaska managed forest land; (b) NGHGI (2019) estimate of Alaska cropland area; (c) NGHGI (2019) estimate of Alaska managed grassland area; (d) NLCD (2001) land cover estimates (Forests is combination of deciduous forest, evergreen forest; Cropland is cultivated crops; Grassland is shrub/scrub, grasslands/herbaceous, pasture/hay; Wetlands is combination of woody wetlands and emergent herbaceous wetlands; Settlements is combination of developed, open space/low/medium/high intensity; Other is combination of perennial ice snow, bare rock/sand/clay, moss); (e) Values from Table 6-9, NGHGI (2019), using a combination of NOAA C-CAP and NLCD land cover data.

Note that Table T-41 covers only managed land. The NGHGI defines managed land as: forest lands with active fire protection and timber harvesting; grasslands located in counties with livestock; and all settlements and croplands (Ogle et al. 2018). Grassland and forest land that do not meet this initial criteria are considered managed if located within 10 km of a road, railway, or settlement. All wetlands are considered managed because there is insufficient data to determine which wetlands are artificially changed or created by human activity. Protected lands and lands with active/past resource extraction are considered managed.

There are 46.3 million hectares of unmanaged U.S. lands, the majority of which are grassland, and forest in Alaska, and which are further than 10 km from any roads or railways (Ogle et al. 2018). Limiting GHG inventories to managed landscapes could create challenges in the future by not accounting for wildfires, permafrost melt, coastal wetland destruction, and other events that result in substantial GHG emissions on unmanaged lands.

OMITTED GHG FLUXES IN ALASKA

Here we estimate the omitted GHG flux categories in Alaska, with calculations annotated in the notes of Table T-42. More information on these calculations can be found in the Spreadsheet Appendix.

Table T-42: Omitted GHG flux estimates for Alaska

NGHGI Category	Sub-category	Emission factor ($MMT CO_2e/Mha$)	Land area (Mha)	GHG emissions ($MMT CO_2e$)
Ag. soil mgmt.	N_2O, other N additions, cropland and grassland	0.426 [a]	45.524 [b]	18.10
Ag. soil mgmt.	N_2O, drained organic soils	4.42 [c]	0.163 [d]	0.721
Cropland	Soil C stock change, drained organic soils	24.06 [e]	0.00009 [f]	0.002
Cropland	Soil C stock change, mineral soils	0.15 [g]	0.0286 [b]	-0.004
Grassland	Soil C stock change			30.50 [h]
Grassland	Non-CO_2, grassland fires		0.227 [i]	0.389 [j]
Wetlands	C stock change			17.52 [h]
Wetlands	CH_4 emissions			23.17 [h]
Settlements	C stock change, drained organic soils	46.43 [k]	0.0001 [l]	0.005
Settlements	N_2O, drained organic soils	9.39 [m]	0.0001 [l]	0.001
Total				**90.40**

Negative values indicate CO_2 sequestration. All tables discussed here and not otherwise cited refer to NGHGI (2019), Annex 3 and Chapter 6. (a) Total 2017 Tier 1 and Tier 3 N_2O emissions on mineral soils from managed manure additions, other organic amendments, crop/grass residue N, mineralization of SOM (Table A-207, A-208) divided by total 2012 mineral soil cropland and grassland area, plus portion of indirect N_2O emissions attributable to other N additions (Table A-216, A-217); (b) Total Alaska cropland and grassland mineral soil area, assuming 15% of Alaska grassland is organic soil (Table T-41 in this document); (c) Total N_2O from drainage of organic soils on cropland and grassland (Table A-212) divided by total area of drained organic soils (Table A-201); (d) percent of total cropland and grassland area on organic soils (Table A-199), multiplied by total Alaska cropland and grassland area from Table T-41 in this document. Note these calculations implicitly assume all (estimated) organic soil in Alaskan grasslands is drained, a strong assumption; (e) Total CO_2 emissions from drained organic soils (Table A-214) divided by total area of drained organic soils (Table A-201); (f) Total Alaska cropland area multiplied by percent of total cropland and grassland area on organic soils (Table A-199). Note we do not include CO_2 from grassland drained organic soils to avoid any overlap with grassland soil C stock change estimates from Zhu and McGuire (2016) (see part h); (g) Total CO_2 flux from soil carbon stock change on cropland mineral soils (Table A-209) divided by area of cropland mineral soils (Table 6-7, Table A-199); (h) NGHGI (2018) Table 6-15 (Zhu and McGuire 2016 results overlaid on managed Alaska land base), Grassland soil C stock change includes methane emissions, Wetlands include all wetlands (not just coastal); (i) Calculated using Alaska Department of Natural Resources total area affected by fires 2009-2017, scaling up total Alaska managed forest fires (Table A-233) to total forest fires (managed + unmanaged) and subtracting this total from total fire area to find total grassland fire area, and scaling this down to managed grassland fire area. For detailed calculations see Spreadsheet Appendix; (j) Area of burned grassland is multiplied by 14.3 tons dry matter/ha (IPCC 2006 default for shrublands – this is a higher amount of biomass than assumed for grassland fires in CONUS) and multiply dry matter by CH_4 and N_2O default emissions factors (IPCC 2006); (k) Total C flux from drained organic soils on U.S. settlements (Table 6-68) divided by U.S. settlement area on organic soils (Table 6-70); (l) U.S. settlement area on organic soils (Table 6-70) divided by total U.S. settlement area (Table 6-6) net Alaska settlement area (Table T-41 in this document), multiplied by Alaska settlement area; (m) Total direct and indirect N_2O from drained organic soils on U.S. settlements (Table 6-77) divided by U.S. settlement area on organic soils (Table 6-70).

Note that most of the omitted Alaska GHG fluxes are estimated to be quite small, with the exception of soil carbon stock changes in grasslands and wetlands, and methane emissions from wetlands. These categories cover large areas of Alaska and also are at risk for significant changes due to climate change, as noted by Zhu and McGuire (2016).

Note than many of the omitted GHG fluxes calculated in other parts of the Technical Appendix do not include Alaska, for example non-CO_2 from woody biomass burning in grassland fires, which would increase total omitted GHG fluxes in Alaska.

OMITTED GHG FLUXES IN HAWAII

Here we estimate the omitted GHG flux categories in Hawaii, with calculations annotated in the notes of Table T-43. More information on these calculations can be found in the Spreadsheet Appendix.

Table T-43: RESULTS – Omitted GHG flux estimates for Hawaii

NGHGI Category	Sub-category	Emissions factor (MMT CO_2e/Mha)	Land area (Mha)	GHG emissions (MMT CO_2e)
Ag. soil mgmt.	N_2O, other N additions	0.426 [a]	1.375 [b]	0.585
Forests	C stock change			6.857 [c]
Forests	Non-CO_2, forest fires		0.00005 [d]	0.0001 [e]
Wetlands	C stock change			– [f]
Total				**7.44**

All tables discussed here and not otherwise cited refer to NGHGI (2019), Annex 3 and Chapter 6. (a) Total 2017 Tier 1 and Tier 3 N_2O emissions on mineral soils from managed manure additions, other organic amendments, crop/grass residue N, mineralization of SOM (Table A-207, A-208) divided by total 2012 mineral soil cropland and grassland area, plus portion of indirect N_2O emissions attributable to other N additions (Table A-216, A-217); (b) Total Hawaii cropland and grassland area (Table T-41 in this document); (c) Taken directly from Selmants et al. (2017), Table 6.7, including native dry forest, invaded dry forest, native mesic-wet forest, invaded mesic-wet forest; (d) Calculated using Selmants et al. (2017), covering dry forest, mesic forest, and wet forest burned area; (e) Each forest type burned area is multiplied by amount of combusted dry matter, derived from Selmants et al. (2017), Table 5.7, these values are then multiplied by CH_4 and N_2O default emissions factors (IPCC 2006); (f) Wetlands comprise around 0.2% of land area in Hawaii (Selmants et al. 2017) and there is no additional evaluation of wetland carbon stock change or methane emissions in Selmants et al. (2017) or further evaluation of Hawaii wetland types. Therefore we did not attempt to estimate this small flux.

Omitted GHG fluxes for Hawaii are smaller than Alaska but still substantial, deriving largely from omitting carbon stock change in Hawaiian forests.

Note that even though Hawaii non-CO_2 from grassland fires are included in the NGHGI, since the data is based on the Monitoring Trends in Burn Severity (MTBS) dataset, and this dataset is known to not cover all fires in Hawaii, the NGHGI values for grassland fires in Hawaii are likely an underestimate. However, the value of the omitted GHG flux is likely to be small, as demonstrated with the total flux from forest fire non-CO_2 (Table T-43).

OMITTED GHG FLUXES IN PUERTO RICO

We do not estimate any omitted GHG fluxes from U.S. Territories as a whole. However, Puerto Rico comprises 85% of the land area of U.S. Territories. A 2014 report from the Center for Climate Strategies (CCS) estimated an economy-wide GHG baseline for Puerto Rico which includes N_2O from cropland soils, carbon stock change from woody perennials on cropland, and forestry and urban tree carbon stock change (Table T-44). There are many missing GHG categories not covered in the CCS report, including carbon stock change in cropland soils, any fluxes in grasslands, carbon and non-CO_2 emissions from drained organic soils, any forest carbon fluxes other than above and below ground carbon, and settlement soils. However, we include available estimates here for context and prioritization.

Table T-44: Center for Climate Strategies estimates for Puerto Rico land-related GHG fluxes, 2010

GHG flux categories	GHG emissions (MMT CO_2e)
N_2O from cropland soils	0.13
Woody perennial cropland carbon stock change	-0.28
Forest carbon stock change	-0.56
Urban tree carbon stock change	-0.12
Total	-0.83

Negative values indicate CO_2 sequestration.

FOREST CARBON STOCK CHANGE IN INTERIOR ALASKA

In the 2019 NGHGI, forest carbon stock change estimates for interior Alaska were included for the first time. This added 24.5 million hectares of forest to the U.S. forest carbon inventory. The 2019 NGHGI does not list forest carbon stock change values separately for Alaska, nor does it separately report uncertainty calculations for interior Alaska.

The interior Alaska method differs from that in the contiguous United States and coastal Alaska. While it still relies on plot-level FIA measurements starting in 2014, a gain-loss method is used rather than the stock change method used in coastal Alaska and the contiguous United States. The FIA plot density in interior Alaska is 1/5 of that in the contiguous U.S. and coastal Alaska.

We did not attempt to attribute uncertainty for the Alaska forestry calculations, given limited information on data and methods. Many of the model error attribution estimates we calculate for the contiguous U.S. methods will apply to Alaska, and the smaller sampling rate will likely result in higher sampling error.

7 Appendix – Survey Results

Table A-1: Cropland and grassland Tier 3 expert elicitation, full results for Section 2, Prompts 1-3

Category	Research need	Rating	Total # of responses
Empirical data needs	Build research site networks of N_2O and CH_4 soil fluxes and soil C measurements resulting from a diverse range of management activities (Schmidt et al. 2011).	4.27	16
Empirical data needs	Establish a national soil monitoring network to produce for a full and consistent dataset of soil carbon measurements over time (Schmidt et al. 2011; Spencer et al. 2011).	4.27	16
Soil model development and intermodel comparison	Improve model validation with updated comparisons to empirical regression models that are based on field experiments (Brevik et al. 2015; Kuzyakov 2010; Paustian et al. 2016; Schmidt et al. 2011; Stockmann et al. 2013).	4.18	17
Soil model development and intermodel comparison	Increase collaboration among model developers, shifting to a community-centered, open-source approach and integrating databases and computational tools (Paustian et al. 2016; Schmidt et al. 2011)	4.09	17
Primary soil research	Influence of microbial activity – and other physicochemical and biological influences – on decomposition of organic matter/carbon, nitrogen and phosphorous cycling (Conant et al. 2011; Kuzyakov 2010; Schmidt et al. 2011; Schimel & Schaeffer 2012).	4.00	19
Soil model development and intermodel comparison	Expand model inter-comparison programs (such as AgMIP) to identify cross-cutting sources of uncertainty and opportunities for model improvement and cross-pollination.	4.00	17
Empirical data needs	Obtain additional measurements of N_2 production and losses from denitrification to clarify optimal N_2/ N_2O ratios for both modeling purposes and proper fertilizer management (Bakken & Frostegård 2017; S. DelGrosso, personal communication, October 1, 2018; Well et al. 2018).	4.00	16
Soil model development and intermodel comparison	Reconcile bottom-up, process-based accounting of N_2O fluxes with newer top-down methods (e.g., atmospheric inversions) that capture N cycling from the global and regional perspective (Butterbach-Bahl 2013; Chen et al. 2016; DelGrosso et al. 2008; S. DelGrosso, personal communication, October 1, 2018; Nevison et al. 2018).	3.91	17
Empirical data needs	Obtain additional experimental data on above-ground N uptake or direct measurements of N_2O for cross-site optimization/better validation of large scale model estimates of soil N_2O fluxes (S. DelGrosso, personal communication, October 1, 2018; Ehrhardt et al. 2018; Reay et al. 2012; Van Groenigen et al. 2010).	3.91	16
Primary soil research	Contribution of biochar feedstock type, production temperature and process, application rate, interactions with N sources, and more to the observed reduction of soil N_2O emissions through biochar application (Cayuela et al. 2014).	3.83	18
Primary soil research	Permafrost biogeochemistry and its role in driving nitrogen availability, as well as the freeze/thaw process of permafrost soil microbes, which may contribute to N_2O emissions (Butterbach-Bahl 2013; Schmidt et al. 2011).	3.83	18
Soil model development and intermodel comparison	Shift from theoretical carbon pools to a mechanistic model that consider soil biological and physiochemical processes and drivers (Paustian et al. 2016; Stockmann 2013).	3.82	17
Soil model development and intermodel comparison	Incorporate simultaneous simulation of nitrification and denitrification, topographical effects on soil hydrology, and other N dynamics, to more accurately reflect the complexities in N cycling (Butterbach-Bahl 2013).	3.82	17
Primary soil research	Impact of warming temperatures on stores of carbon in permafrost, including the relationship between accelerated decomposition and increased nitrogen availability (Rumpel & Kogel-Knabner 2010; Schmidt et al. 2011).	3.75	19

Empirical data needs	Incorporate spatial data to better understand soil structure and its influence on soil biota, including microbial access to soil organic carbon (Schmidt et al. 2011; Stockmann et al. 2013).	3.73	16
Soil model development and intermodel comparison	Model the entire soil profile, representing changes in processes and rate constants associated with depth of soil or carbon inputs (such as mineral associations and root and dissolved organic inputs). Include explicit depth resolution for decomposition and transport (Schmidt et al. 2011).	3.64	17
Empirical data needs	Expand use of novel tools like isotopes, inhibitors and molecular techniques which can help to better characterize and quantify N_2O soil processes (Butterbach-Bahl 2013; Cayuela et al. 2014).	3.64	16
Primary soil research	Importance of soil moisture in driving process-specific loss rates of N_2O (e.g., anaerobic conditions like increased soil water content or soil compaction stimulates denitrification and N_2O emissions, as has been observed in conservation agriculture practices like low-till or no-till) (Butterbach-Bahl 2013; Met et al. 2018).	3.58	18
Primary soil research	Impact of soil texture on CH_4 emissions – better understanding the diminished emissions observed in clay soils versus silt soils (Brye et al. 2013).	3.58	18
Soil model development and intermodel comparison	Include more microbial mechanisms to allow determination of soil carbon responses to global climate change (e.g., vary microbial growth efficiency instead treating it as a fixed parameter) (Stockmann et al. 2013; Wider et al. 2013).	3.55	17
Soil model development and intermodel comparison	Consider impact of freeze/thaw on CO_2 and CH_4 production. Develop soil columns to represent different stages of O_2 limitation and freezing effects, such as inundation, permafrost thaw and thermakarst (Schmidt et al. 2011).	3.55	17
Empirical data needs	Generate high-quality data from new technologies, like soil measurements taken from sensors, to feed into models (Schmidt et al. 2011).	3.55	16
Empirical data needs	Integrate databases and computational tools for advanced molecular SOM research (Schmidt et al. 2011).	3.55	16
Primary soil research	The spatial architecture of the soil in the context of a soil ecosystem and how soil structure impacts microbial access to soil organic carbon (Paustian et al. 2016).	3.50	19
Primary soil research	The properties and dynamics of carbon in deep soils, beyond the top 30 cm (Dungait et al. 2012; Rumpel & Kogel-Knabner 2010; Schmidt et al. 2013).	3.50	19
Primary soil research	Understanding the underlying processes that influence the accretion, turnover and stability of soil organic matter in subsoil horizons (which have been observed to have a long turnover time) (Paustian 2016; Rumpel & Kogel-Knabner 2010; Schmidt et al. 2013).	3.50	19
Primary soil research	Influence of temperature changes on the rate of N_2O reaction. Specifically, why N_2O release is accelerated by rising temperatures as compared to falling temperatures and how this impacts modeling (Butterbach-Bahl 2013).	3.50	18
Empirical data needs	Utilize top-down methodology, like atmospheric observations of trace-gas concentrations from satellite based measurements in combination with inverse modelling to estimate fluxes between the atmosphere and land surfaces, to verify against models based on observed management activities (Ogle et al. 2015; Schmidt et al. 2011).	3.45	16
Empirical data needs	Engage land-use stakeholders, tapping into their empirical knowledge of land management strategies, which can be combined with soil/climate maps, remote sensing and process-based models to calculate emissions (Paustian et al. 2016).	3.45	16
Empirical data needs	Perform additional CH_4 studies that assess CH_4 fluxes to better validate large scale modeled estimates of CH_4 fluxes.	3.45	16
Soil model development and intermodel comparison	Create and model microbial functional types, similar to how plant functional types are considered (Schmidt et al. 2011).	3.36	17
Primary soil research	Impact of soil erosion on the soil carbon cycle and its role in the storage or loss of carbon (Brevik et al. 2015).	3.33	19

Soil model development and intermodel comparison	Model the decay rate as a function of substrate properties and spatial positions in microenvironment, microbial activity and soil conditions (Schmidt et al. 2011).	3.27	17
Soil model development and intermodel comparison	Expand application of existing models with validated parameters to include more diverse soil systems like peatlands and other organic soils (Dungait et al. 2012).	3.27	17
Soil model development and intermodel comparison	Separately characterize above-ground and below-ground inputs (Schmidt et al. 2011).	3.27	17
Primary soil research	Relationship between microbial carbon use efficiency and temperature; how carbon use efficiency declines or improves in response to temperature; and the influence of carbon use efficiency on soil carbon losses. (Alison et al. 2010).	3.25	19
Primary soil research	Role of microbial biomass in soil organic matter turnover as a fundamental process affecting soil-priming effects. Consideration of microbes as not only a pool but as a driver of the turnover (Kuzyakov 2010).	3.25	19
Primary soil research	Role of soil fungi in denitrification, through additional field studies or using new technologies (Butterbach-Bahl 2013).	3.25	18
Primary soil research	Influence of temperature change on CH_4 fluxes from rice production. Reconciling sources of accelerated CH_4 emissions, like higher rates of root decay, to sources of reduced CH_4 emissions, like overheating, sterility, and diminished precipitation (Zhang et al. 2016).	3.25	18
Soil model development and intermodel comparison	Shift towards landscape scale modelling of soil organic matter dynamics for more comprehensive view of the agricultural landscape, as opposed to soil-profile/plot scale (Fellman et al. 2010).	3.18	17
Soil model development and intermodel comparison	Model the interactions between litter decay and soil organic formation (Cotrufo et al. 2012; Dungait et al. 2012).	3.18	17
Soil model development and intermodel comparison	Incorporate water management types outside of continuous flooding when measuring CH_4 (this is specific to DayCent) (U.S. National Greenhouse Gas Inventory 2018).	3.18	17
Soil model development and intermodel comparison	Replace the concept of increasing recalcitrance due to decomposition and synthesis with organic matter cycling into and out of microbial biomass (Schmidt et al. 2011).	3.09	17
Soil model development and intermodel comparison	Include physical processes that follow non-normal probability distributions and density-dependent terms for organic matter and microbial biomass (Schmidt et al. 2011).	3.09	17
Primary soil research	The significance of roots and root exudates to the soil carbon stock changes[i] (39); clarity on the mechanisms underlying retention of root-derived carbon; and impact of fresh root inputs on decomposition and community composition (Schmidt et al. 2011).	3.08	19
Primary soil research	Role of soil organism diversity in reducing loss of N through N_2O emissions (Wagg 2014).	3.08	18
Primary soil research	Microbial regulation of enzyme activities, particularly in response to temperature, precipitation and other climatic events (Burns et al. 2013).	3.00	19
Primary soil research	Formalizing through new models or modules the emerging understanding that soil organic matter is composed of inherently stable and chemically unique compounds, deviating from the traditional "humification" model that prioritizes physical/molecular properties of organic matter and sequences the decomposition of individual carbon pools in accordance with first order kinetics (Allison et al. 2010; Paustian et al. 2016; Schimel & Schaeffer 2012; Stockman et al. 2013).	3.00	19
Primary soil research	Potential role of soil inhabiting archaea in producing N_2O emissions (Butterbach-Bahl 2013).	3.00	18
Soil model development and intermodel comparison	Water regimes of rice agricultural systems may be highly variable, but are often estimated through an assumption of homogenous water regimes. Shift to subgrid variability in water regimes to better capture CH_4 emissions (Zhang et al. 2016).	2.82	17
Empirical data needs	Improve accounting of N_2O and CH_4 emissions from the growing aquaculture industry, which remains poorly understood (Bridgham et al. 2013; Reay et al. 2012).	2.82	16

Primary soil research	Impact of short- and long-term effects of biochar and other fire-derived organic matter amendments on soil carbon cycling and sequestration, including impacts on soil biota and soil chemical properties (Brevik et al. 2015; Lehmann et al. 2011).	2.67	19
Soil model development and intermodel comparison	Include CH_4 fluxes from land use types other than rice agriculture, like natural and managed grassland systems (DelGrosso et al. 2000).	2.64	17
Soil model development and intermodel comparison	Improve model representations of rice varieties and iron reduction/oxidation to better estimate CH_4 emissions in rice fields (Zhang et al. 2016).	2.64	17
Primary soil research	Mechanistic processes underlying the impact of biochar on reducing N_2O emissions: factors including, but not limited to, microbial immobilization of inorganic N in soil, alleviation of anoxic conditions, increased sorption capacity of biochars, reduction of N uptake by plants, and formation and stability of soil aggregates (Cayuela et al. 2014; Clough et al. 2013; Singh et al. 2010).	2.50	18
Empirical data needs	Utilize RNA technology to analyze microbial diversity, adding breadth to traditional DNA analyses of microbial activity (Baldrian et al. 2012; Brevik et al. 2015).	2.45	16
Empirical data needs	Incorporate new information sources, like recently developed soil DNA databases (Paustian et al. 2016; Stockmann et al. 2013).	2.45	16
Primary soil research	Decomposition pathways of biochar and other fire-derived organic matter (Schmidt et al. 2011).	2.33	19
Primary soil research	CH_4 and N_2O emissions from aquaculture (currently this is an omitted flux in the NGHGI) (Reay et al. 2012).	2.33	18
Soil model development and intermodel comparison	Include input pathway for fire-derived carbon (Schmidt et al. 2011).	2.27	17
Soil model development and intermodel comparison	Add aromatic compounds to soil organic matter types (Schmidt et al. 2011).	2.09	17

8 References

Allison, S.D., Wallenstein, M.D., Bradford, M.A. (2010). Soil-carbon response to warming dependent on microbial physiology. *Nature Geoscience, 3*, 336-340.

Arneth A., Harrison S.P., Zaehle, S., Tsigaridis. K., Menon, S., Bartlein, P.J.,…Vesala, T. (2010). Terrestrial biogeochemical feedbacks in the climate system. *Nature Geoscience, 3*, 525-532.

Bakken L.R., Frostegård Å. (2017). Sources and sinks for N_2O, can microbiologist help to mitigate N_2O emissions? *Environ Microbiol 19*, 4801–480

Bechtold, W. A., Patterson, P. L., Eds. (2005). The enhanced Forest Inventory and Analysis program – National sampling design and estimation procedures. (Gen. Tech. Rep. SRS-80). Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station. 85 p.

Blackard, J., Finco, M., Helmer, E., Holden, G., Hoppus, M., Jacobs, D., et al. (2008). Mapping U.S. forest biomass using nationwide forest inventory data and moderate resolution information. Remote Sensing of Environment, 112:1658-1677.

Brevik, E.C., Cerda, A., Mataix-Solera, J., Pereg, L., Quinton, J.N., Six, J., Van Oost, K. (2015). The interdisciplinary nature of SOIL. *SOIL, 1*(1), 117-129.

Bridgham, S.D., Cadillo-Quiroz, H., Keller, J.K., Zhuang, Q. (2012). Methane emissions from wetlands: biogeochemical, microbial, and modeling perspectives from local to global scales. *Global Change Biology, 19*(5), 1325-1346.

Brye, K.R., Rogers, C.W., Smartt, A.D., Norman, R. K. (2013). Soil Texture Effects on Methane Emissions From Direct-Seeded, Delayed-Flood Rice Production in Arkansas. *Soil Science, 178*(10). 519-529.

Burns, R.G., DeForest, J.L., Marxsen, J., Sinsabaugh, R.L., Stromberger, M.E., Wallenstein, M.D., Weintraub, M.N., Zoppini, A. (2013). Soil enzymes in a changing environment: current knowledge and future directions. *Soil Biology and Biochemistry, 58*, 216-234.

Burrill, E. A., Wilson, A. M., Turner, J. A., Pugh, S. A., Menlove, J., Christensen, G., Conkling, B. L., David, W. (2017). The Forest Inventory and Analysis Database: FIA Database description and user guide version 7.2 for Phase 2. U.S. Department of Agriculture, Forest Service. 946 p. [Online]. Available at: http://www.fia.fs.fed.us/library/database-documentation/.

Butterbach-Bahl, K., Baggs, E.M., Dannenmann, M., Kiese, R., Zechmeister-Boltenstern, S. (2013). Nitrous oxide emissions from soils: how well do we understand the processes and their controls? *Philosophical Transactions of the Royal Society, 368*(1621).

Byrd, K. B., Ballanti, L. R., Thomas, N. M., Nguyen, D. K., Holmquist, J. R., Simard, M., Windham-Myers, L., Schile, L. M., Parker, V. T., … Castaneda-Moya, E. (2017). Biomass/Remote Sensing dataset: 30m resolution tidal marsh biomass samples and remote sensing data for six regions in the conterminous United States: U.S. Geological Survey data release, https://doi.org/10.5066/F77943K8.

Byrd, K. B., Ballanti, L., Thomas, N., Nguyen, D., Holmquist, J.R., Simard, M., Windham-Myers, L. (2018). A remote sensing-based model of tidal marsh aboveground carbon stocks for the conterminous United States. ISPRS Journal of Photogrammetry and Remote Sensing 139: 255-271.

Cayuela, M.L., van Zwieten, L., Singh, B.P., Jeffrey, S., Roig, A., Sanchez-Monedero, M.A. (2014). *Agriculture, Ecosystems & Environment, 191*, 5-16.

Center for Climate Strategies. (2014). Puerto Rico GHG Baseline Report. http://drna.pr.gov/wp-content/uploads/2017/05/Puerto-Rico-GHG-2014.pdf

Chen, Z., Griffis, T.J., Millet, D.B., Wood, J.D., Lee, X., Baker, J.M., Xiao, K., Turner, P.A., Chen, M., Zobitz, J., Wells, K.C. (2016). Partitioning N_2O emissions within the US Corn Belt using an inverse modeling approach. *Global Biogeochemical Cycles*, *30*(8), pp.1192-1205.

Clough, B., Curzon, M., Domke, G., Russell, M., Woodall, C. (2016). Climate-driven trends in stem wood density of tree species in the eastern United States: Ecological impact and implications for national forest carbon assessments. Global Ecology and Biogeography, 26:1153-1164.

Clough, T.J., Condron, L.M., Kammann, C., Muller, C. (2013). A Review of Biochar and Soil Nitrogen Dynamics. *Agronomy, 3(*2), 275-293.

Conant, R.T., Ryan, M.G., Agren, G.I., Birge, H.E., Davidson, E.A., Eliasson, P.E.,…Bradford, M.A. (2011). Temperature and soil organic matter decomposition rates–synthesis of current knowledge and a way forward. *Global Change Biology, 17*(11), 3392-3404.

Cotrufo, M.F., Wallenstein, M.D., Boot, C.M., Denef, K., Paul, E. (2012). The Microbial Efficiency-Matrix Stabilization (MEMS) framework integrates plant litter decomposition with soil organic matter. *Global Change Biology, 19*(4), 988-995.

Coulston, J. W., Wear, D. N., Vose, J. M. (2015). Complex forest dynamics indicate potential for slowing carbon accumulation in the southeastern United States. *Scientific Reports, 5*, 8002, doi: 10.1038/srep08002.

DelGrosso, S., Ogle, S.M., Parton, W.K., Bredit, F.J. (2009). Estimating uncertainty in N_2O emissions from U.S. cropland soils. *Global Biogeochemical Cycles, 24*.

DelGrosso, S.J, Parton, W.J., Mosier, A.R., Ojima, D.S., Potter, C.S., Borken, W.,…Smith, K.A. (2000). General CH_4 oxidiation model and comparisons or CH_4 oxidation in natural and managed systems. *Global Biogeochemical Cycles, 14*(4): 999-1019.

DelGrosso, S.J., Parton, W.J., Mosier, A.R., Ojima, D.S., Potter, C.S., Borken, W.,…Smith, K.A. (2000). General CH oxidation model and comparisons of CH_4 oxidation in natural and managed systems. *Global Biogeochemical Cycles, 14*(4), 999-1019.

Division of Geological & Geophysical Surveys (DGGS), Alaska Department of Natural Resources (1993–2015) Alaska's Mineral Industry Report (1997–2014). Alaska Department of Natural Resources, Fairbanks, AK.

Domke, G. M., Perry, C. H., Walters, B. F., Nave, L. E., Woodall, C. W., Swanston, C. W. (2017). Toward inventory-based estimates of soil organic carbon in forests of the United States. *Ecological Applications, 27(*4), 1223–1235.

Domke, G. M., Perry, C. H., Walters, B. F., Woodall, C. W., Russell, M. B., Smith, J. E. (2016). Estimating litter carbon stocks on forest land in the United States. *Science of the Total Environment 557–558*, 469–478.

Domke, G. M., Woodall, C. W., Smith, J. E. (2011). Accounting for density reduction and structural loss in standing dead trees: Implications for forest biomass and carbon stock estimates in the United States. *Carbon Balance and Management 6*, 14, 1–11.

Domke, G. M., Woodall, C. W., Smith, J. E., Westfall, J. A., McRoberts, R. E. (2012). Consequences of alternative tree-level biomass estimation procedures on U.S. forest carbon stock estimates. *Forest Ecology and Management, 270*, 108–116.

Dooley, Kerry, J. W. (2018). Forests of east Texas, 2016. (Resource Update FS–151). Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station. 4 p.

Dowle, M., Srinivasan, A. (2019). Data.table: Extension of 'data.frame'. (R package version 1.12.2). https://CRAN.R-project.org/package=data.table.

Dungait, J.A., Hopkins, D.W., Gregory, A.S., Whitmore, A.P. (2012). Soil organic matter turnover is governed by accessibility not recalcitrance. *Global Change Biology, 18*(6), 1781-1796.

Dutaur, L., Verchot, L. (2007). A global inventory of the soil CH_4 sink. *Global Biogeochemical Cycles*, 21.

Ehrhardt, F., Soussana, J.F., Bellocchi, G., Grace, P., McAuliffe, R., Recous, S., Sándor, R., Smith, P., Snow, V., de Antoni Migliorati, M., Basso, B. (2018). Assessing uncertainties in crop and pasture ensemble model simulations of productivity and N_2O emissions. *Global change biology, 24*(2), 603-e616.

Fellman, J.B., Hood, E., Spencer, R.M. (2010). Fluorescence spectroscopy opens new windows into dissolved organic matter dynamics in freshwater ecosystems: A review. *Limnology and Oceanography, 55*(6), 2452-2462.

Forest Products Laboratory. (2010). Wood handbook—Wood as an engineering material. (Gen. Tech. Rep. FPL-GTR-190). Madison, WI: U.S. Department of Agriculture, Forest Service, Forest Products Laboratory. 508 p.

Fry, J., Xian, G., Jin, S., Dewitz, J., Homer, C., Yang, L., Barnes, C., Herold, N., J. Wickham. (2011). Completion of the 2006 National Land Cover Database for the Conterminous United States, *Photogrammetric Engineering and Remote Sensing*, *77*(9), 858-864.

Genz, A., Bretz, F., Miwa, T., Mi, X., Leisch, F., Scheipl, F., Bornkamp, B., Maechler, M., Hothorn, T. (2019). mvtnorm: Multivariate Normal and t Distributions. (R package version 1.0-10). http://CRAN.R-project.org/package=mvtnorm

Harmon, M. E., Woodall, C. W., Fasth, B., Sexton, J., Yatkov, M. (2011). Differences between standing and downed dead tree wood density reduction factors: A comparison across decay classes and tree species. (Res. Paper NRS-15). Newtown Square, PA: U.S. Department of Agriculture, Forest Service. 44 p.

Heath, L. S., Hansen, M. H., Smith, J. E., Smith, W. B., Miles, P. D. (2009). Investigation into calculating tree biomass and carbon in the FIADB using a biomass expansion factor approach. In: McWilliams, W.; Moisen, G.; Czaplewski, R., comps. 2008 Forest Inventory and Analysis (FIA) Symposium; 2008 October 21–23: Park City, UT. Proc. RMRS-P-56CD. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Homer, C., Dewitz, J., Fry, J., Coan, M., Hossain, N., Larson, C., Herold, N., McKerrow, A., VanDriel, J. N., Wickham, J. (2007). Completion of the 2001 National Land Cover Database for the Conterminous United States. *Photogrammetric Engineering and Remote Sensing, 73*(4), 337–341.

Homer, C., Dewitz, J., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N., Wickham, J., Megown, K. (2015). Completion of the 2011 National Land Cover Database for the conterminous United States – Representing a decade of land cover change information. *Photogrammetric Engineering and Remote Sensing, 81*(5), 345–354.

Hu, Z., Lee, J.W., Chandran, K., Kim, S., Khanal, S.K. (2012). Nitrous oxide (N_2O) emission from aquaculture: a review. *Environmental Science & Technology, 46*(12): 6470-80.

IPCC. (2019). 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. https://www.ipcc-nggip.iges.or.jp/public/2019rf/index.html

IPCC. (2006). 2006 IPCC Guidelines for National Greenhouse Gas Inventories. The National Greenhouse Gas Inventories Programme, The Intergovernmental Panel on Climate Change. [H.S. Eggleston, L. Buendia, K. Miwa, T. Ngara, and K. Tanabe (eds.)]. Hayama, Kanagawa, Japan.

IPCC. (2007). Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, 996 pp.

IPCC. (2014). 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands. Hiraishi, T., Krug, T., Tanabe, K., Srivastava, N., Baasansuren, J., Fukuda, M. and Troxler, T.G. (eds.). Published: IPCC, Switzerland.

Jenkins, J. C., Chojnacky, D. C., Heath, L. S., Birdsey, R. A. (2003). National-scale biomass estimators for United States tree species. *Forest Science, 49*(1), 12–35.

Jenkins, J. C., Chojnacky, D. C., Heath, L. S., Birdsey, R. A. (2004). Comprehensive Database of Diameter-based Biomass Regressions for North American Tree Species. (Gen. Tech. Rep. NE-219). Newtown Square, PA: U.S. Department of Agriculture, Forest Service. 48 p.

Kuzyakov, Y. (2010). Priming effects: Interactions between living and dead organic matter. *Soil Biology and Biochemistry, 42*(9), 1363-1371.

Lehmann, J., Rillig, M.C., Thies, J., Masiello, C.A., Hockaday, W.C., Crowley, D. (2011). Biochar effects on soil biota–a review. *Soil Biology and Biochemistry*, 43(9), 1812-1836.

Lu, D., Chen, Q., Wang, G., Liu, L., Li, G., Moran, E. (2016). A survey of remote sensing-based aboveground biomass estimation methods in forest ecosystems. International Journal of Digital Earth, 9(1):63-105.

Ma, W., Domke, G., D'Amato, A., Woodall, C., Walters, B., Deo, R. (2018). Using matrix models to estimate aboveground forest biomass dynamics in the eastern USA through various combinations of LiDAR, Landsat, and forest inventory data. Environmental Research Letters, 13:125004.

Marden, R. M., Lothner, D. C., Kallio, E. (1975). Wood and bark percentages and moisture contents of Minnesota pulpwood species. (Res. Paper NC-114). St. Paul, MN: U.S. Department of Agriculture, Forest Service. 14 p.

McRoberts, R., Chen, Q., Domke, G., Stahl, G., Saarela, S., Westfall, J. (2016). Hybrid estimators for mean aboveground carbon per unit area. Forest Ecology and Management, 378:44-56.

Mei, K., Wang., Z., Huang, H., Zhang, C., Shang, X., Dahlgren, R.A.,…Xia, F. (2018). Stimulation of N_2O emission by conservation tillage management in agricultural lands: a meta-analysis. *Soil & Tillage Research*, 86-93.

Mersmann, O., Trautmann, H., Steuer, D., Bornkamp, B. (2018). truncnorm: Truncated Normal Distribution. (R package version 1.0-8). https://CRAN.R-project.org/package=truncnorm

Miles, P. D., Smith, W. B. (2009). Specific gravity and other properties of wood and bark for 156 tree species found in North America. (Res. Note NRS-38). Newtown Square, PA: U.S. Department of Agriculture, Forest Service. 39 p.

MTBS Data Summaries. (2015). MTBS Project, data last revised April 2015. USDA Forest Service/U.S. Geological Survey. Available online at http://mtbs.gov/data/search.html

Nair P., Nair V. (2003). Carbon Storage in North American Agroforestry Systems (Chapter 5). *Advances in Agronomy, 108*, 237-307.

Nevison, C., Andrews, A., Thoning, K., Dlugokencky, E., Sweeney, C., Miller, S., Saikawa, E., Benmergui, J., Fischer, M., Mountain, M., Nehrkorn, T. (2018). Nitrous oxide emissions estimated with the CarbonTracker-Lagrange North American regional inversion framework. *Global Biogeochemical Cycles*, *32*(3), pp.463-485.

Nowak, D. J., Greenfield, E. J., Hoehn, R. E., Lapoint, E. (2013). Carbon storage and sequestration by trees in urban and community areas of the United States. *Environmental Pollution, 178*, 229-236. doi:10.1016/j.envpol.2013.03.019

Nowak, D., Greenfield, E. (2010). Sustaining America's Urban Trees and Forests.

Nowak, D.J., Crane, D.E., Stevens, J.C., Hoehn, R.E., Walton, J.T., Bond, J. (2008). A Ground-Based Method of Assessing Urban Forest Structure and Ecosystem Services. *Arboriculture & Urban Forestry, 2008*. 34(6):347–358.

Nusser, S. M., Goebel, J. J. (1997). The national resources inventory: a long-term multi-resource monitoring programme. *Environmental and Ecological Statistics 4*, 181–204.

Ogle, S. M., Domke, G. M., Kurz, W. A., Rocha, M. T., Huffman, T., Swan, A., Smith, J. E., Woodall, C. W., Krug, T. (2018). Delineating managed land for reporting national greenhouse gas emissions and removals to the United Nations framework convention on climate change. *Carbon Balance and Management 13*(9), 1–13.

Ogle, S., Domke, G., Kurz, W., Rocha, M., Huffman, T., Swan, A., Smith, J., Woodall, C., Krug, T. (2018). Delineating managed land for reporting national greenhouse gas emissions and removals to the United Nations framework convention on climate change. Carbon Balance and Management, 13:9.

Ogle, S.M., Breidt, F.J., Easter, M., Williams, S., Paustian, K. (2007). An empirically based approach for estimating uncertainty associated with modelling carbon sequestration in soils. *Ecological Modelling, 205*,453-463.

Ogle, S.M., Breidt, F.J., Easter, M., Williams, S., Paustian, K. (2010). Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model. *Global Change Biology, 16,* 810-822.

Ogle, S.M., Breidt, F.J., Eve, M.D., Paustian, K. (2003). Uncertainty in estimating land use and management impacts on soil organic carbon storage for US agricultural lands between 1982 and 1997. *Global Change Biology, 9,* 1521-1542.

Ogle, S.M., K. Davis, T. Lauvaux, A. Schuh, D. Cooley, T.O. West, L.S. Heath, N.L. Miles, S. Richardson, F.J. Breidt, J.E. Smith, J.L. McCarty, K.R. Gurney, P. Tans, A.S. Denning. (2015). An Approach for Verifying Biogenic Greenhouse Gas Emissions Inventories with Atmospheric CO_2 Concentration Data. *Environmental Research Letters 10*:034012.

Ohrel, S.B., in press. Policy perspective on the role of forest sector modeling. Journal of Forest Economics.

Paustian, K., Lehmann, J., Ogle, S., Reay, D., Robertson, G.P, Smith, P. (2016). *Climate-smart soils.* Nat*ure, 532,* 49-57.

R Core Team. (2018). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Raile, G.K. (1982). Estimating stump volume. (Res. Paper NC-224). St. Paul, MN: U.S. Department of Agriculture, Forest Service. 7 p.

Reams, G. (2017). Forest Inventory and Analysis Budget and Strategic Plan Implementation. U.S. Forest Service. http://www.ncasi.org/wp-content/uploads/2019/02/Reams.pdf

Reay, D.S., Davidson, E.A., Smith, K.A., Smith, P., Melilo, J., Dentener, F., Crutzen, P.J. (2012). Global agriculture and nitrous oxide emissions. *Nature, 2,* 410-416.

Ruefenacht, B., Finco, M. V., Nelson, M. D., Czaplewski, R., Helmer, E. H., Blackard, J. A., Holden, G. R., Lister, A. J., Salajanu, D., Weyermann, D., Winterberger, K. (2008). Conterminous U.S. and Alaska Forest Type Mapping Using Forest Inventory and Analysis. USDA Forest Service - Forest Inventory and Analysis Program & Remote Sensing Applications Center. Available online at: http://data.fs.usda.gov/geodata/rastergateway/forest_type/

Rumpel, C., Kogel-Knabner, I. (2010). Deep soil organic matter—a key but poorly understood component of terrestrial C cycle. *Plant and Soil, 338,* 143-158.

Schimel, J.P., Schaeffer, S.M. (2012). Microbial control over carbon cycling in soil. *Terrestrial Microbiology, 3,* 1-10.

Schmidt, M.W., Torn, M.S., Abiven, S., Dittmar, T., Guggenberger, G., Janssens, I.A.,…Trumbore, S.E. (2011). Persistence of soil organic matter as an ecosystem property. *Nature, 478,* 49–56.

Schroeder, P. (1994). Carbon Storage Benefits of Agroforestry Systems. *Agroforestry Systems, 27*: 89-97.

Selmants, P.C., Giardina, C.P., Jacobi, J.D., and Zhu, Zhiliang, eds. (2017). Baseline and projected future carbon storage and carbon fluxes in ecosystems of Hawai'i: U.S. Geological Survey Professional Paper 1834, 134 p., https://doi.org/10.3133/pp1834.

Singh, B.P., Hatton. B.J., Singh, B., Cowie, A.L., Kathuria, A. (2009). Influence of Biochars on Nitrous Oxide Emission and Nitrogen Leaching from Two Contrasting Soils. *Journal of Environmental Quality Abstract, 20*(4), 1224-1235.

Skog, K. E. (2008). Sequestration of carbon in harvested wood products for the United States. *Forest Products Journal, 58*(6), 56–72.

Skog, K. E., Pingoud, K., Smith, J.E. (2004). A method countries can use to estimate changes in carbon stored in harvested wood products and the uncertainty of such estimates. *Environmental Management, 33*(1), S65–S73.

Smith, J. E., Heath, L. S., Jenkins, J. C. (2003). Forest volume-to-biomass models and estimates of mass for live and standing dead trees of U.S. forests. (Gen. Tech. Rep. NE-298). Newtown Square, PA: United States Department of Agriculture Forest Service.

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. Soil Survey Geographic (SSURGO) Database. Accessed January 10, 2019.

Spencer, S., Ogle, S.M., Breidt, F.J., Goebel, J.J., Paustian, K. (2011). Designing a national soil carbon monitoring network to support climate change policy: a case example for US agricultural lands. *Greenhouse Gas Measurement and Management, 1*(3-4), 167-178.

Stockmann, U., Adams, M.A., Crawford, J.W., Field, D.J., Henakaarchchi, N., Jenkins, M.,…, Zimmerman, M. (2013). The knowns, known unknowns and unknowns of sequestration of soil organic carbon. *Agriculture, Ecosystems and Environment, 164*, 80-99.

U.S. National Marine Fisheries Service. (2017). Fisheries of the United States, 2016. U.S. Department of Commerce, NOAA Current Fishery Statistics No, 2016. Available at: https://www.fisheries.noaa.gov/resource/document/fisheries-united-states-2016-report

Udawatta, R., Jose, S. (2012). Carbon Sequestration Potential of Agroforestry Practices in Temperate North America. *Agroforestry Systems, 86*, 225-242.

United States Department of State. (2016). Second Biennial Report of the United States of America. Washington, DC.

United States Environmental Protection Agency. (2018). Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990 – 2016. Washington, DC.

United States Environmental Protection Agency. (2019). Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990 – 2017. Washington, DC.

United States White House. (2016). U.S. Mid-Century Strategy for Deep Decarbonization. Washington, DC.

USDA. (2013). Soil Survey Staff. Rapid Carbon Assessment (RaCA) project. United States Department of Agriculture, Natural Resources Conservation Service. Available online. June 1, 2013 (FY2013 official release).

USDA Forest Service. (2015). Forest Inventory and Analysis National Program: FIA Data Mart. Washington, DC: U.S. Department of Agriculture Forest Service. Available online at http://apps.fs.fed.us/fiadb- downloads/datamart.html.

USDA Forest Service. (2018). Forest Inventory and Analysis National Program: FIA Data Mart. Washington, D.C. Available online at: https://apps.fs.usda.gov/fia/datamart/datamart.html. Accessed 25 August 2018.

USDA. (2012). Agroforestry USDA Reports to America, Fiscal Years 201-2012 – Comprehensive Version. Retrieved December 20, 2018 from https://www.usda.gov/sites/default/files/documents/usda-reports-to-america-comprehensive.pdf

USDA. (2014). U.S. Census of Agriculture. Available at: https://www.nass.usda.gov/Publications/AgCensus/2012/#full_report

USDA Natural Resources Conservation Service. (2015). Summary Report: 2012 National Resources Inventory, Natural Resources Conservation Service, Washington, D.C., and Center for Survey Statistics and Methodology, Iowa State University, Ames, Iowa. Available online at: http://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcseprd396218.pdf.

USGS. (1991–2016). Minerals Yearbook: Peat (1994–2016). United States Geological Survey, Reston, VA.

USGS. (2018). Mineral Commodity Summaries: Peat (2018). United States Geological Survey, Reston, VA.

van den Boogaart, K. G., Tolosana-Delgado, R., Bren, M. (2018). compositions: Compositional Data Analysis. (R package version 1.40-2). https://CRAN.R-project.org/package=compositions

Van Groenigen, J.W., Velthof, G.L., Oenema, O., Van Groenigen, K.J., Van Kessel, C. (2010). Towards an agronomic assessment of N_2O emissions: a case study for arable crops. *European Journal of Soil Science, 61*(6), 903-913.

Wagg, C., Bender, S.F., Widmer, F., van der Heijden, M.G.A. (2014). Soil biodiversity and soil community composition determine ecosystem multifunctionality. *Proceedings of the National Academy of Sciences of the United States of America, 111*(14), 5266-5270.

Watanabe, S., Hajima, T., Sudo, K., Nagashima, T., Takemura, T., Okajima, H.,…Kawamiya, M. (2011). MIROC-ESM 2010: Model description and basic results of CMIP5-20c3m experiments. *Geoscientific Model Development, 4,* 845-872.

Wear, D. N., Coulston, J. W. (2015). From sink to source: Regional variation in U.S. forest carbon futures. *Scientific Reports 5*, 16518. https://doi.org/10.1038/srep16518.

Well, R., Burkart, S., Giesemann, A., Grosz, B., Reent Köster, J., Lewicka-Szczebak, D. (2018). Improvement of the 15N gas flux method for in situ measurement of soil denitrification and its product stoichiometry. *Rapid Communications in Mass Spectrometry*

White House. (2015). Climate Change and the Land Sector: Improving Measurement, Mitigation and Resilience of our Natural Resources. https://obamawhitehouse.archives.gov/sites/whitehouse.gov/files/documents/Climate_Change_and_Land_Sector_Report_2015.pdf

Wickham, J., Stehman, S., Gass, L., Dewitz, J., Sorenson, D., Granneman, B., Poss, R., Baer, L. (2017). Thematic accuracy assessment of the 2011 National Land Cover Database (NLCD). https://pubs.er.usgs.gov/publication/70185756

Wieder, W.R., Bonan, G.B., Allison, S.D. (2013). Global soil carbon projections are improved by modelling microbial processes. *Nature Climate Change, 3,* 909-912.

Woodall, C. W., Coulston, J. W., Domke, G. M., Walters, B. F., Wear, D. N., Smith, J. E., Andersen, H.-E., Clough, B. J., Cohen, W. B., Griffith, D. M., Hagen, S. C., Hanou, I. S., Nichols, M. C., Perry, C. H., Russell, M. B., Westfall, J. A., Wilson, B. T. (2015). The U.S. Forest Carbon Accounting Framework: Stocks and Stock Change, 1990–2016. (Gen. Tech. Rep. NRS-154). Newtown Square, PA: U.S. Department of Agriculture, Forest Service. 60 p.

Woodall, C. W., Heath, L. S., Domke, G. M., Nichols, M. C. (2011). Methods and equations for estimating aboveground volume, biomass, and carbon for trees in the U.S. Forest Inventory, 2010. (Gen. Tech. Rep. NRS-88). Newtown Square, PA: U.S. Department of Agriculture, Forest Service. 34 p.

Zhang, B., Tian, H., Ren, W., Tao, B., Lu, C., Yang, J.,…Pan, S. (2016). Methane emissions from global rice fields: Magnitude, spatiotemporal patterns, and environmental controls. *Global Biogeochemical Cycles, 30*(9), 1246-1263.

Zhu, Zhiliang, McGuire, A.D., eds. (2016). Baseline and projected future carbon storage and greenhouse-gas fluxes in ecosystems of Alaska: U.S. Geological Survey Professional Paper 1826, 196 p., http://dx.doi.org/10.3133/pp1826.