Reducing climate policy risk:

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

September 2019

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References can be found at the end of the Technical Appendix.

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Executive Summary

This report identifies the largest sources of uncertainty and omitted greenhouse gas (GHG) fluxes in the land use, land use change, and forestry (LULUCF) sections of the U.S. National Greenhouse Gas Inventory (NGHGI). We provide recommendations for how to address the highest priority uncertainties and omissions, including: address sampling uncertainty from extrapolating forest carbon plot measurements to total U.S. forest area; estimate carbon fluxes on non-forest landscapes in Alaska; support additional field measurements for forest carbon model parameters; improve modeling methods for urban tree carbon; and support primary research and field measurements for soil carbon modeling. We underline the need to move towards a nationally comprehensive land sector GHG monitoring system that handles all U.S. land types and regions consistently for all carbon pools, overcoming challenges of using different datasets and models across forests, croplands, grasslands, settlements, and wetlands.

Why uncertainty in the LULUCF sector matters

Every year, U.S. LULUCF removes a net 600 to 800 million metric tons (MMT) carbon dioxide (CO_2) from the atmosphere, reducing economy-wide GHG emissions by 9 to 13 percent annually (Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2017 [NGHGI], 2019). There is, however, significant uncertainty in calculating annual LULUCF emissions. Indeed, the LULUCF sector contributes over 70 percent of the total uncertainty in U.S. annual economy-wide GHG emissions estimates, with a total LULUCF uncertainty range of over 600 MMT of CO_2 equivalents (CO_2e) (NGHGI 2019).[1]

While not a new challenge, this uncertainty continues to have a profound impact on climate policy planning and tracking. Setting national GHG reduction targets, reporting on progress towards climate targets, and demonstrating climate success all depend on confidently tracking GHG emissions from local to global scales. In turn, uncertainty in GHG emissions numbers can create climate policy risk. Policy makers may be hesitant to set ambitious emissions reduction targets if they are worried shifts in LULUCF GHG estimates could make achieving policy goals more difficult. This policy risk is especially important as the United States and other countries set post-2025 targets under the United Nations Paris Agreement. Reducing the uncertainty associated with LULUCF emissions could allow for:

– More ambitious climate policy planning,

– Improved confidence in climate policy tracking and claiming success in meeting emissions reduction goals, and

– Perhaps most importantly, an ability to keep up with the rapid changes on U.S. landscapes resulting from climate change, including increasing droughts, floods, storms, and fire. The U.S. GHG inventory will need to be nimble, capturing large GHG changes that occur over short periods of time with relatively high confidence.

We stress nothing discussed below undermines the basic findings of the NGHGI to date, nor does it call into question the scientific underpinning of the need to act on climate change. The U.S. LULUCF GHG inventory is thorough in its uncertainty estimation, which is one of the reasons its uncertainty values are large. This thorough analysis and reporting is a good thing. Recognizing and quantifying uncertainty are critical for interpreting GHG emissions data, and the more information we have about uncertainty the better. GHG inventories that report low uncertainty values (or no uncertainty at all) may have low uncertainty, but it is more likely they are not appropriately accounting for all sources of uncertainty. Hopefully, one outcome of this report is that stakeholders around the world will pay more attention to how GHG inventories handle uncertainty issues and prioritize better uncertainty estimation.

How this report builds on the U.S. GHG inventory

The U.S. NGHGI calculates GHG emissions and sequestered CO_2 (collectively, GHG fluxes) from LULUCF by splitting total U.S. land area into six land categories: forest, cropland, grassland, settlement, wetland, and other, and then further divides into subcategories of land area that has remained in the same category for the past 20 years (e.g., *Forest Remaining Forest*) and land area that has moved from one category to another at some point

1. The 600 MMT CO_2e uncertainty range refers to the difference between the upper and lower bounds of the 95 percent confidence interval for the LULUCF sector as reported in the NGHGI (2019). This means the reader can be 95 percent certain that the true LULUCF GHG sequestration total is contained within this range of values, conditional on a number of assumptions. We describe this and other uncertainty metrics in more detail in the rest of this report, including *Section 2. Uncertainty and Accuracy in the Greenhouse Gas Inventory*.

in the past 20 years (e.g., *Forest Converted to Cropland*). For each land subcategory, the NGHGI calculates all or some subset of GHG fluxes from the following categories:

– Changes in carbon stocks (an increase in carbon stock results in net CO_2 sequestration, while a decrease in carbon stocks results in net CO_2 emissions) across six carbon pools: aboveground living biomass, below-ground living biomass, dead biomass, litter, soils, and harvested wood products
– CO_2, CH_4, and N_2O emissions from drained organic soils
– N_2O emissions from soils due to nitrogen application and other natural processes
– CH_4 and N_2O emissions from wildfires and prescribed burns
– CH_4 and N_2O from wetlands and peatland management

For each GHG flux calculation and for each land subcategory, the NGHGI reports both a flux estimate as well as a 95 percent confidence interval, which provides a measurement of uncertainty for the flux estimate. The NGHGI notes sources of uncertainty and describes how 95 percent confidence intervals are calculated for each flux. Different land categories have different datasets and models that support estimating the above GHG fluxes, so there are inconsistencies in calculation methods across land categories. The NGHGI generally recognizes these inconsistencies and notes some of them for future improvements. Not all GHG fluxes are calculated for all land categories—sometimes this is due to the nature of the land type, but other times it is due to lack of data or appropriate methods, in which case we refer to this as an "omitted flux." The NGHGI recognizes nearly all omitted fluxes that we discuss in this report and notes that many of them are priorities for inclusion in future inventories.

This report supports ongoing improvements to the U.S. LULUCF GHG inventory by:

– Identifying the amount of uncertainty attributable to individual equations, datasets, and inputs for each GHG flux calculation, in order to prioritize opportunities for reducing uncertainty;
– Estimating the scale of omitted GHG fluxes, in order to prioritize efforts for their inclusion in future inventories; and
– For the largest sources of uncertainty and omitted GHG fluxes, developing recommendations for additional data collection, model development, and other opportunities to reduce uncertainty and include omitted fluxes in the U.S. LULUCF GHG inventory.

The scope of this report covers the entire LULUCF chapter of the NGHGI (Chapter 6) as well as soil management sections of the Agriculture chapter (Chapter 5), which going forward we refer to collectively as the LULUCF sections of the NGHGI or the LULUCF GHG inventory.[2] We calculate both omitted GHG fluxes as well as attribute sources of uncertainty across every calculation in the LULUCF sections of the NGHGI, evaluating over 90 uncertainty elements and GHG fluxes. We are not attempting to recalculate total uncertainty of the LULUCF GHG inventory but rather quantify and rank individual sources of uncertainty.

Report methods

To identify the largest sources of uncertainty in the LULUCF sections of the NGHGI, we undertook the following steps:

– We reviewed every GHG flux calculation and, where possible, recreated the calculation using available data and models.
– For GHG fluxes where we could recreate the calculation methods used, we identified all inputs, parameters, and model components (collectively, elements) that have potential to contribute uncertainty to the final result and use literature review or assumptions to estimate the uncertainty of those individual elements. Then, we estimated uncertainty attribution through the contribution index method *(see Equation 1 in the Technical Appendix)*.
– For GHG fluxes where we could not recreate the calculation method, we used uncertainty attribution results from literature or expert survey to identify the largest sources of uncertainty.
– Uncertainty elements we could not quantify, due to lack of data or complexity of the calculation method, are listed in Table 2 below.

To estimate omitted GHG fluxes, we employed the following methods:

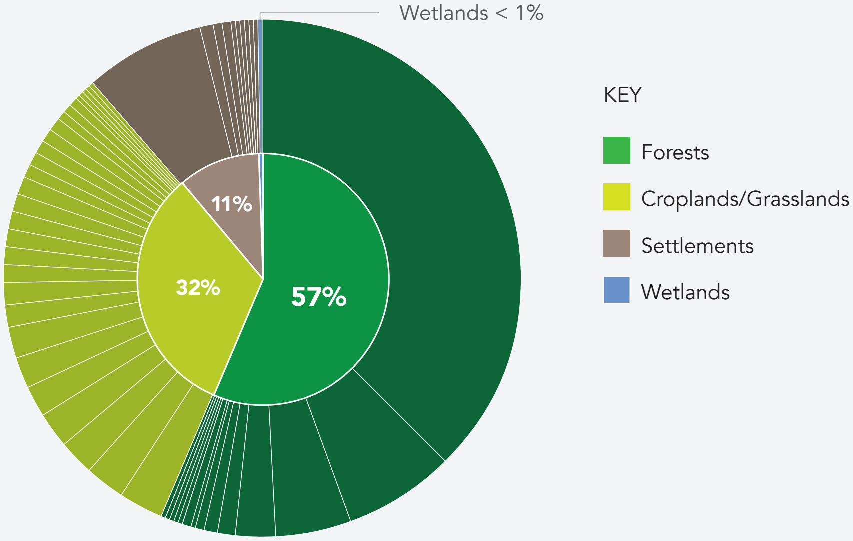
– We identified omitted GHG flux categories by comparing included GHG flux estimates across all land subcategories and reviewing GHG inventory guidance from the Intergovernmental Panel on Climate Change (IPCC 2006; IPCC 2014; IPCC 2019).
– We then performed a literature review to identify activity data and emission factors to estimate first-order or rough estimates of the omitted GHG flux wherever possible. Details on each omitted flux calculation are available in the Technical Appendix.

Our omitted GHG flux values are all rough estimates and are more useful for purposes of prioritizing future work rather than informing actual flux magnitudes. This is not surprising since these fluxes have been omitted from the NGHGI due to lack of data.

2. We include several sections in the Agriculture chapter in our scope because they use the same model (DayCent) as similar sections in the LULUCF chapter, and share common sources of uncertainty.

Figure ES-1: Final project results – Sources of uncertainty in the LULUCF GHG Inventory

The number next to each element represents its contribution to the uncertainty (95% confidence interval) of its respective calculation in units of million metrics tons (MMT) CO_2e. The project team analyzed over 90 uncertainty elements across input datasets, models, and calculation methods for GHG fluxes in forests, croplands, grassland, settlements, and wetlands, using statistical and survey methods. It is not valid to add together all the uncertainty attribution values to find total uncertainty of the NGHGI.



Forests

434 Forest ecosystem (sampling error)
78 Forest ecosystem modeling parameter (volume coefficients)
54 Forest ecosystem modeling parameter (wood & bark specific gravities)
29 Non-CO2 from forest fires (fuel availabilities for wildfires and prescribed fires in conterminous US)
12 Harvested Wood Products (solid wood products data)
11 Harvested Wood Products (solid wood products conversion to carbon)
6 Non-CO2 from forest fires (emission factors)
4 Harvested Wood Products (paper data)
4 Non-CO2 from forest fires (combustion factor for conterminous US)
3 Harvested Wood Products (paper conversion to carbon)
3 Harvested Wood Products (paper decay limit)
2 Forest ecosystem modeling parameter (biomass component ratio coefficients)
2 Harvested Wood Products (solid wood products discard rate)
2 Harvested Wood Products (solid-waste disposal sites decay rate)
2 Forest ecosystem modeling parameter (sapling adjustment factor)
1 Harvested Wood Products (paper discard rate)
1 N2O from N additions (direct N2O)
1 Forest ecosystem modeling parameter (total aboveground biomass as diameter-based regression)
1 Harvested Wood Products (solid wood products decay limit)
0 Drained organic soils (C stock change)
0 Non-CO2 from forest fires (burned area)
0 Non-CO2 from forest fires (fuel availability – combustion factor for Alaska)
0 Forest ecosystem modeling parameter (bark as a percentage of wood volume)
0 Forest ecosystem modeling parameter (structural loss adjustment for standing dead trees)
0 N2O from N additions (indirect N2O)
0 Drained organic soils (N2O)
0 Drained organic soils (dissolved CO2)
0 Drained organic soils (CH4)
0 Forest ecosystem modeling parameter (stump volume coefficients)
0 Forest ecosystem modeling parameter (density reduction factor for standing dead trees)

Croplands/Grasslands

31 Tier 3 DayCent (soil properties)
29 Tier 3 DayCent (leaching, runoff, and volatilization)
26 Tier 3 DayCent (organic matter formation and decomposition)
24 Tier 3 DayCent (nitrification and denitrification processes)
23 Tier 3 DayCent (manure and other organic fertilizer applications)
23 Tier 3 DayCent (tillage: conventional, reduced, no-till)
22 Tier 3 DayCent (fertilization management)
16 Tier 3 DayCent (soil and water temperature regimes by layer)
15 Tier 3 DayCent (grazing intensity)
14 Tier 3 DayCent (plant growth and phenology)
14 Tier 3 DayCent (irrigation)
13 Tier 3 DayCent (harvest, variable residue removal)
12 Tier 3 DayCent (crop types)
12 Tier 3 DayCent (flooding/drainage for rice cultivation)
12 Tier 3 DayCent (Enhanced Vegetation Index (EVI) data)
11 Tier 3 DayCent (daily weather data)
10 Tier 3 DayCent (organic amendments for rice cultivation)
10 Tier 3 DayCent (crop sequences, rotation)
9 Tier 3 DayCent (methanogenesis)
8 Tier 3 DayCent (burning, grasslands)
7 Tier 3 DayCent (surrogate data)
7 Drained organic soils (C stock change)
5 Tier 3 DayCent (NRI time series)
4 Tier 1 & 2 (carbon loss rate, organic soils)
3 Tier 1 & 2 (tillage factor)
3 Tier 1 & 2 (land use change factor)
3 Tier 3 DayCent (expansion factors)
3 Non-CO2 from grassland fires (fuel availability)
1 Tier 1 & 2 (land use, NRI data)
0 Tier 1 & 2 (tillage practices, CTIC data)
0 Tier 1 & 2 (improved pasture)
0 Non-CO2 from grassland fires (burned area)
0 Non-CO2 from grassland fires (emission factors)
0 Tier 1 & 2 (reference carbon stocks)
0 Tier 1 & 2 (input factor)

Settlements

87 Urban Trees (gross to net sequestration ratio)
7 Urban Trees (gross sequestration rate)
7 Urban Trees (urban area)
6 Yard trimmings and food scraps (food scraps multiplier)
4 Urban Trees (tree coverage percentage)
4 Yard trimmings and food scraps (percent carbon stored)
2 Yard trimmings and food scraps (moisture content)
2 Yard trimmings and food scraps (yard trimmings multiplier)
1 N2O from N additions (direct N2O)
1 Drained organic soils (C stock change)
1 Yard trimmings and food scraps (initial carbon content)
1 Yard trimmings and food scraps (fraction of total weight)
1 Yard trimmings and food scraps (decay rates)
0 N2O from N additions (indirect N2O)

Wetlands

4 Soil C stock change
1 Soil CH4
0 Peatland
0 Aboveground biomass C stock change
0 N2O from aquaculture

Table ES-1. Top 10 sources of uncertainty in the LULUCF GHG Inventory

<table>
<thead>
<tr><th>Land category</th><th>Element</th><th>Contribution to uncertainty (MMT CO_2e)</th><th>Recommendation</th><th>Solution category</th></tr>
</thead>
<tbody>
<tr><td>Forests</td><td>Plot sample error</td><td>434.3</td><td>· Increase re-sampling frequency of existing FIA plots
· Make better use of remote sensing data
· Increase stratification</td><td>Field measurements</td></tr>
<tr><td>Settlements</td><td>Urban tree gross to net sequestration ratio</td><td>86.5</td><td>· Align urban tree carbon estimation methods with NGHGI forestry methods
· Derive state-specific gross to net sequestration values</td><td>Improved models and methods</td></tr>
<tr><td>Forest</td><td>Forest ecosystem modeling parameters—volume coefficients</td><td>77.7</td><td rowspan="2">· Implement targeted data collection of tree measurements (e.g., tree density, volume, diameter) and carbon content, using stratified random sampling methods</td><td>Field measurements</td></tr>
<tr><td>Forest</td><td>Forest ecosystem modeling parameters—specific gravities</td><td>54.2</td><td>Field measurements</td></tr>
<tr><td>Cropland/ Grassland</td><td>DayCent uncertainty—Soil properties</td><td>31.3</td><td rowspan="3">· Establish more, and more diverse, sites for gathering soil data, and make this data easily accessible to all
· Support collaboration across government and non-government soil science teams
· Prioritize primary research on soil microbial communities and their interactions with carbon and nutrient cycling
· Collect data on tillage practices (potential for CEAP to address)</td><td>Primary research</td></tr>
<tr><td>Cropland/ Grassland</td><td>DayCent uncertainty—Organic matter formation</td><td>25.6</td><td>Primary research</td></tr>
<tr><td>Cropland/ Grassland</td><td>DayCent uncertainty—Tillage (conventional, reduced-, no-till)</td><td>23.4</td><td>Improved data quality</td></tr>
<tr><td>Cropland/ Grassland</td><td>DayCent uncertainty—N leaching, runoff, volatilization</td><td>28.6</td><td rowspan="3">· Support additional research on the N cycle and soil N_2O measurements
· Represent the influence of nitrification inhibitors and slow-release fertilizers on N_2O emissions (planned NGHGI improvement)
· Collect more data on manure/organic fertilizer application (potential for CEAP to address)</td><td>Field measurement</td></tr>
<tr><td>Cropland/ Grassland</td><td>DayCent uncertainty—nitrification and denitrification</td><td>24.1</td><td>Primary research</td></tr>
<tr><td>Cropland/ Grassland</td><td>DayCent uncertainty—Manure and other organic fertilizer</td><td>23.4</td><td>Improved data quality</td></tr>
</tbody>
</table>

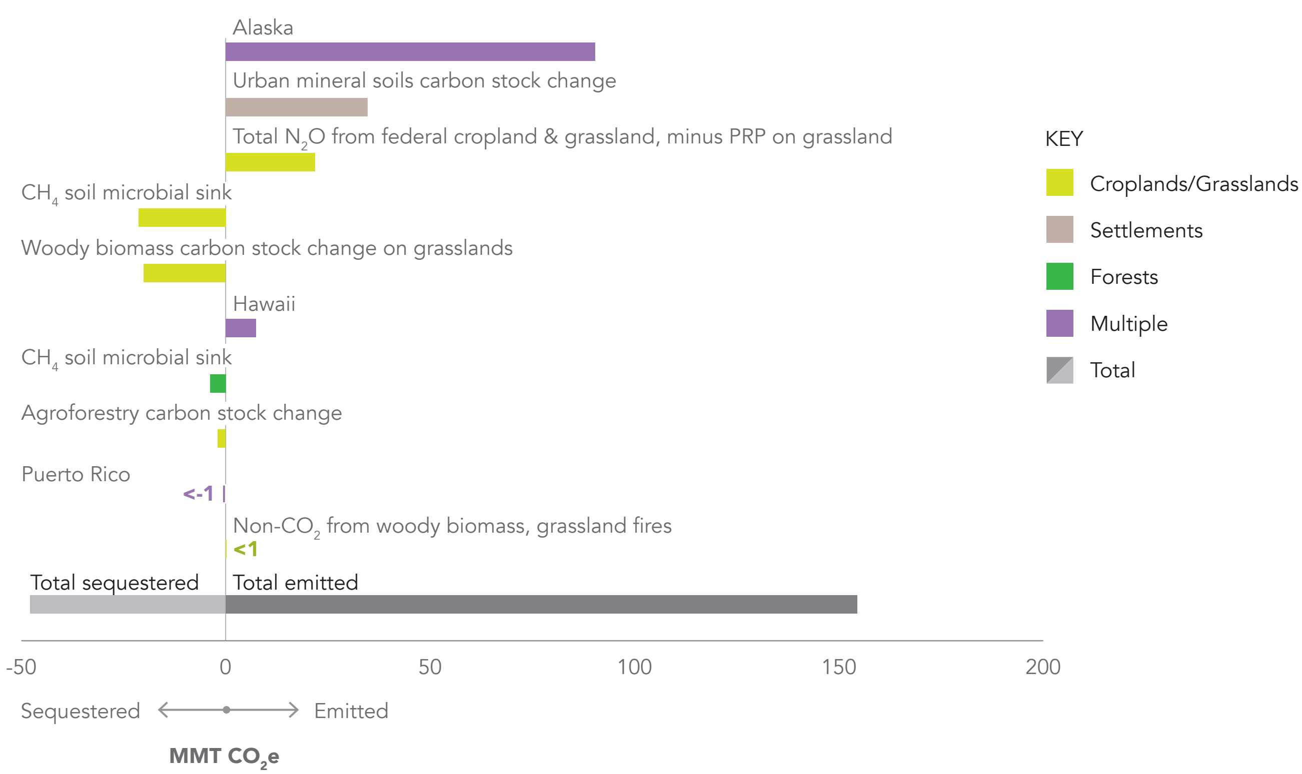
Results

Figure ES-1 shows the results of our uncertainty analysis across all LULUCF components of the NGHGI. The largest sources of uncertainty are relatively well-distributed across land categories. They include:

- Forest plot to population expansion (38 percent of total uncertainty attribution): The largest source of uncertainty, by far, is from extrapolating forest carbon plot measurements to total U.S. forest area, which is a type of sampling uncertainty, also called sampling error.[3]
- Cropland and grassland soil properties, nitrogen processes, tillage, and manure management in the DayCent model (14 percent of total uncertainty attribution): DayCent is a complex biogeochemical model that estimates carbon and nitrogen cycling in soils, providing estimates of CO_2 sequestration and N_2O emissions. Experts indicated the largest sources of uncertainty in DayCent calculations are soil property inputs, such as soil texture and drainage capacity, nitrogen leaching and runoff processes, nitrification/denitrification cycles, and management practices like tillage and manure application.
- Volume coefficients and wood specific gravity parameters (12 percent of total uncertainty attribution): These parameters are used in forest carbon estimation models to convert tree diameter measurements into tree volume and tree biomass values.
- Gross to net sequestration ratio of urban trees (8 percent of total uncertainty attribution): This value estimates the amount of sequestered carbon in urban trees that is lost to downed branches or tree decay. There is a shortage of state-specific ratios, so a national value is used in most state-level calculations, introducing a large amount of uncertainty into the urban trees calculation.

Figure ES-2: Final project results – Omitted GHG fluxes in LULUCF GHG Inventory

In addition to estimating sources of NGHGI uncertainty, we also identified omitted GHG categories. The NGHGI already recognizes most of these gaps and has listed many of them as planned improvements for incorporating into future inventories. We take this recognition one step further by using literature, activity data, and IPCC and U.S.-specific emission factors to provide rough estimates of omitted GHG fluxes. These estimates are meant to help set priorities for addressing omitted fluxes. The magnitude of each flux estimated here is likely to have low accuracy, due to lack of data. Note PRP = Paddock, Rangeland, Pasture manure deposition, the only source of N_2O emissions on federal grasslands currently included in the NGHGI.



3. Note the forestry biomass and deadwood uncertainty attribution results are based on analysis of East Texas only, which we scale nationally. We describe the details of this analysis further in *Section 3: Forests* and in the Technical Appendix, and we provide reasoning for why this approach is valid for purposes of ranking sources of uncertainty.

Our results report the contribution of each uncertainty element to its respective GHG flux calculation's 95 percent confidence interval. A 95 percent confidence interval is a range defined by two end-point values that indicates we can be 95 percent certain that the values within this range include the true GHG flux we are trying to estimate. We are able to convert all uncertainty attribution results into MMT CO_2e by multiplying each uncertainty element's attribution percentage by the magnitude of the GHG flux 95 percent confidence interval. This allows for comparing uncertainty elements across all calculations and all GHG flux categories in the NGHGI. However, it is not valid to add together all the uncertainty attribution values to find total uncertainty of the NGHGI.[4]

Figure ES-2 shows the results of all omitted GHG flux calculations. The largest omission is GHG fluxes from non-forest landscapes in Alaska (90.4 MMT CO_2e), followed by CO_2 emissions from urban mineral soils (34.7 MMT CO_2e), and N_2O emissions from federal cropland and grassland (21.8 MMT CO_2e). Figure ES-2 shows that, on balance, the omitted GHG fluxes are net emissions, indicating LULUCF may not reduce economy-wide GHG emissions as much as currently thought.

Table ES-2. Omitted fluxes in the LULUCF GHG Inventory

Negative value indicates net CO_2 sequestration.

Land category	Element	Omitted flux (MMT CO_2e)	Recommendation	Solution category
Multiple	Alaska	90.4	· Develop new datasets for estimating carbon in Alaska grasslands and wetlands	Data gap
Settlements	Urban mineral soils	34.7	· Implement research program for urban soil carbon measurements	Data gap
Croplands/ Grasslands	N_2O from federal cropland and grassland, minus PRP on grassland	21.8	· Collect data and parameterize DayCent to estimate N_2O fluxes on federal cropland and grassland	Data gap
Croplands/ Grasslands	CH_4 soil microbial sink	-21.3	· Gather data to estimate soil microbial CH_4 sink · Identify methods to attribute CH_4 sink to land management.	Data gap
Forests	CH_4 soil microbial sink	-3.8		Data gap
Croplands/ Grasslands	Woody biomass carbon stock change on grasslands	-20.0	· Use FIA data where possible to include woody biomass on grasslands. · Gather additional data to estimate woody biomass carbon stock change on cropland and grassland and non-CO_2 emissions from fires.	Implementation gap
Croplands/ Grasslands	Agroforestry carbon stock change	-1.9		Data gap
Croplands/ Grasslands	Non-CO_2 from woody biomass, grassland fires	0.2		Field measurement
Multiple	Hawaii	7.4	· Include additional land categories and fluxes from Hawaii and U.S. Territories as budget allows, starting with forest carbon stock change.	Implementation gap
Multiple	Puerto Rico	-0.8		Data gap

4. First, not all of the uncertainty attribution results will be independent. Second, the 95 percent confidence values first must be converted into variance (the average squared difference between each sample point and the average of all sample points), which, assuming independence, could be added across all categories. However, it is not the objective of our study to re-calculate total uncertainty of the LULUCF NGHGI, but rather to attribute sources of uncertainty.

Figure ES-3: Solutions for addressing uncertainty in the LULUCF GHG Inventory

This paper identifies five key solution categories for reducing NGHGI uncertainty: Field measurements; Improved data quality; Primary research; Improved models and methods; and Data gaps. The values correspond to the uncertainty from each element identified in Figure ES-1, aggregated by land sector (Cropland/Grasslands, Forests, Settlements, Wetland). It is not valid to add together all the uncertainty attribution values to get total uncertainty of the NGHGI.

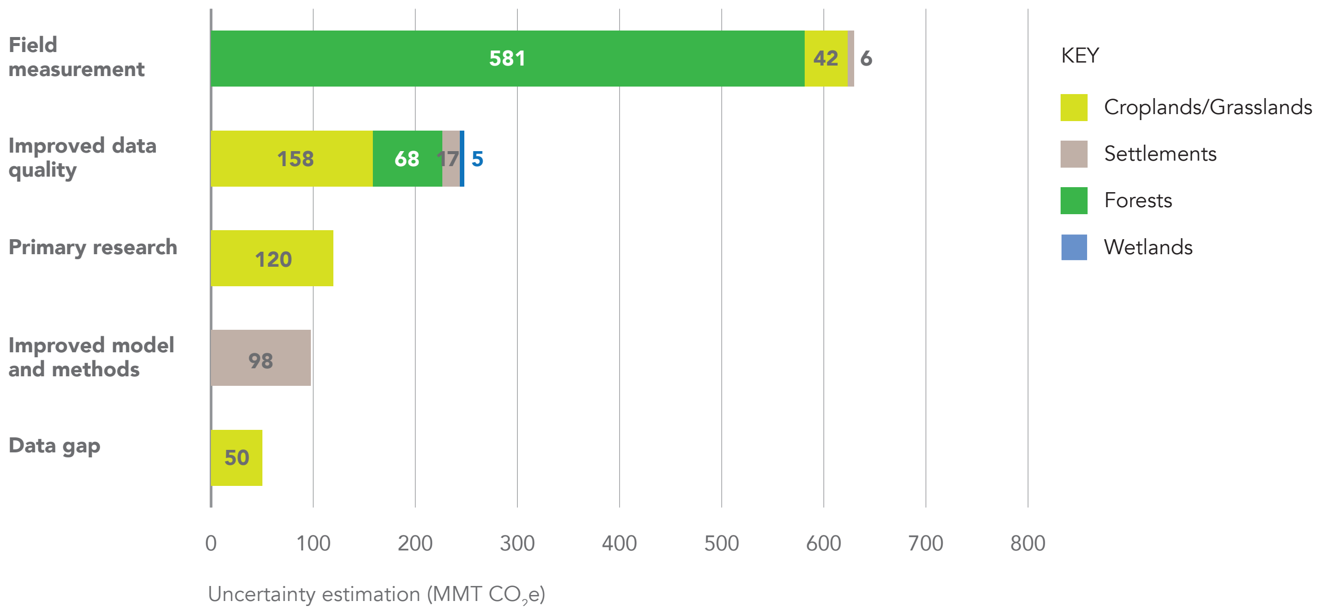
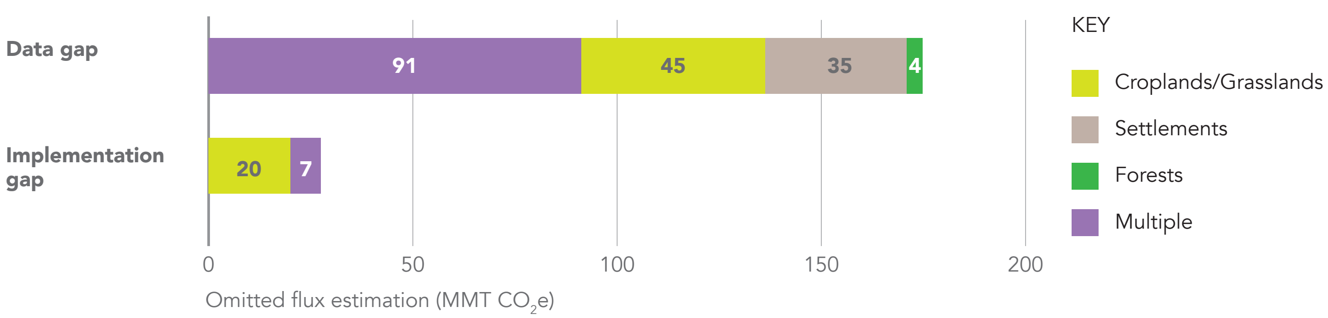


Figure ES-4: Solutions for addressing omitted fluxes in the LULUCF GHG Inventory

This paper identifies two solution categories for addressing omitted fluxes: Data gap; and Implementation gap. The values correspond to the scale of omitted flux from each element identified in Figure ES-2, aggregated by land sector (Cropland/Grasslands, Forests, Settlements, Wetland).



Solutions

To address uncertainty and omitted GHG fluxes, we identified six broad solution categories:

- Field measurements: increasing the number of field measurements or sample plots within existing datasets. For example, forest carbon plot to population sampling error requires intensifying plot sampling within the Forest Inventory and Analysis (FIA) dataset. We encourage broad interpretation of field measurements, which, for example, could include more extensive use of remote sensing data to estimate forest biomass.
- Improved data quality: adding new data and information to existing datasets. For example, adding measurements of fuel availability to National Resource Inventory (NRI) plots could address uncertainty of non-CO_2 emissions from wild fires.
- Primary research: undertaking new primary research to answer basic science questions. For example, a number of soil carbon and nitrogen cycling questions warrant primary research.
- Improved models and methods: addressing aspects of models that contribute significant uncertainty, or developing new models. For example, better harmonizing urban tree carbon models with forest tree carbon estimation methods could address "gross to net sequestration ratio" uncertainty in urban tree carbon calculations.
- Data gap: create new datasets to address gaps in existing datasets and programs. For example, incorporating Alaskan non-forest landscapes into the NGHGI could require entirely new datasets or establishing new plots in existing datasets like FIA or NRI.
- Implementation gap: implementing activities already planned but not yet executed. For example, the NGHGI already provides initial estimates of woody biomass in grasslands, but this is not yet incorporated into official NGHGI reporting.

Figure ES-3 shows the largest opportunities for addressing sources of uncertainty, with the largest need being additional field measurements within existing datasets, particularly for forests.

Similarly, Figure ES-4 presents solution categories for omitted fluxes. The major challenge in estimating omitted fluxes is the lack of necessary data ("data gaps"). Some fluxes, however, are slated for calculation and resource constraints and have simply not allowed for their inclusion in the NGHGI ("implementation gap"), such as estimating carbon in woodland grasslands and estimating forest carbon in Hawaii.

We also compile our top sources of uncertainty and omitted GHG fluxes across the LULUCF GHG inventory and list concrete recommendations for each *(see Table ES-1, Table ES-2)*. The top 10 elements of uncertainty account for nearly three quarters of all calculated uncertainty attribution.

GHG Inventory of the future

The recommendations highlighted above and described throughout this report can meaningfully improve the LULUCF components of the NGHGI. In the longer term, policy makers, researchers, and stakeholders would benefit from overcoming some of the biggest challenges with the current LULUCF inventory system, which is that nearly every land category is handled with different datasets and methods, creating inconsistencies in accounting across carbon pools, land types, and land conversions. To address these issues the United States requires a more dedicated, comprehensive, and publicly-accessible system for estimating land GHG fluxes across all U.S. landscapes. Such a system would require large-scale investment, planning, and political will across federal agencies, but could build on existing datasets like FIA and the NRI. We propose a consistent national GHG accounting system for the land sector, which would include:

- Randomly distributed sample plots across all land types, where carbon measurements are taken across all pools (aboveground biomass, belowground biomass, dead biomass, litter, soil), using gold-standard carbon measurement methods;
- A single, national land representation dataset that is updated annually with information on land use and land cover, as well as variables like forest canopy cover, forest type, crop type, and more;
- Ongoing research to update priority models and parameters;
- Consistent carbon modeling methods across all land types; and
- Public accessibility to raw data and trainings for use of the data and models.

We recommend convening a blue ribbon panel to further develop the national land sector GHG accounting system of the future. Organizing such a panel would follow the process undertaken by the U.S. Forest Service in the 1990s to develop the national annual FIA plot system and dataset. We elaborate on these concepts in Section 8: A Blue Sky Vision.

While we understand that it will never be possible to wholly eliminate uncertainty from the NGHGI, nor is that a meaningful goal, we hope this report helps to identify priorities for reducing uncertainty and improving accuracy while minimizing impacts on budget and staff time at U.S. federal agencies. Taking steps to manage uncertainty and accuracy can increase confidence in the NGHGI both domestically and internationally while improving policy-making capacity and reducing risk for ambitious climate policy goals.

Introduction

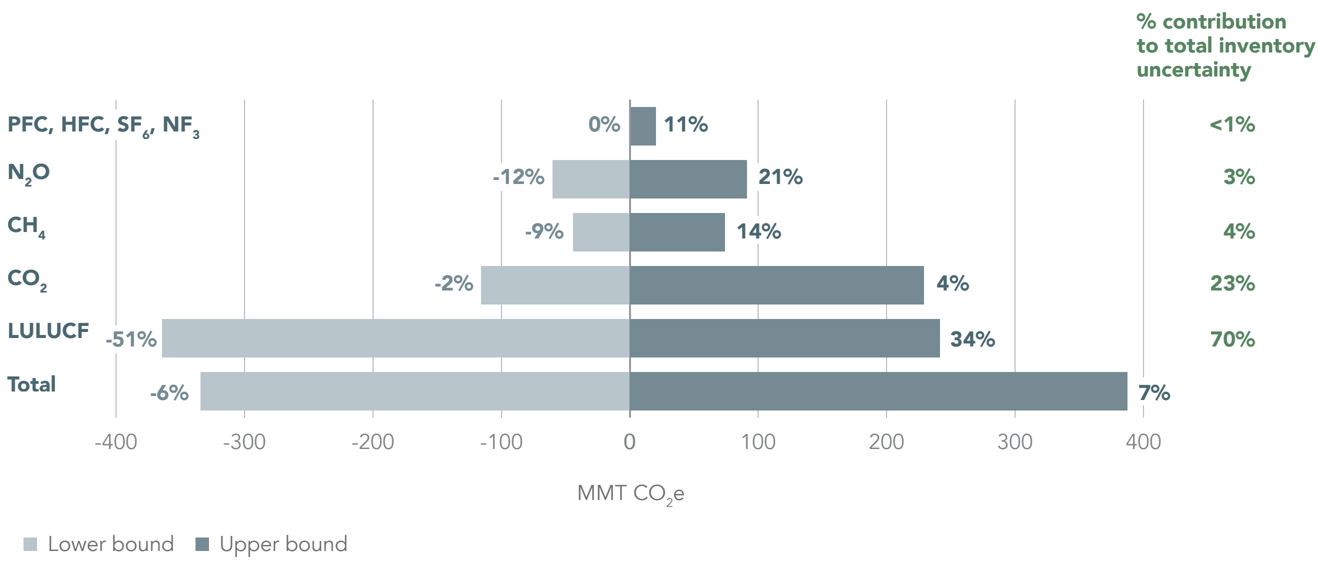
Every year, land use, land use change, and forestry (LULUCF) in the United States removes a net 600 to 800 million metric tons (MMT) carbon dioxide (CO_2) from the atmosphere, reducing economy-wide greenhouse gas (GHG) emissions by 9 to 13 percent (Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2017 [NGHGI], 2019).[5] There is, however, significant uncertainty in calculating annual LULUCF GHG fluxes. The LULUCF sector contributes over 70 percent of the total uncertainty in U.S. annual economy-wide GHG emissions estimates *(see Figure 1).*

This report supports ongoing improvements to the U.S. LULUCF GHG inventory by:

- Identifying the amount of uncertainty attributable to individual equations, datasets, and inputs for each GHG flux calculation, in order to prioritize opportunities for reducing uncertainty;
- Identifying and estimating the scale of omitted GHG fluxes, in order to prioritize efforts for their inclusion in future inventories; and
- For the largest sources of uncertainty and omitted GHG fluxes, developing recommendations for additional data collection, model development, and other opportunities to reduce uncertainty and include omitted fluxes in the U.S. LULUCF GHG inventory.

Figure 1: Percentage of total uncertainty in U.S. GHG inventory by gas and sector (NGHGI 2019)

Bars indicate the 95 percent confidence interval ("error bars") for each category, as reported in the NGHGI (2019). The percentages at the ends of the error bars represent the magnitude of the one-direction 95 percent confidence interval divided by the mean emissions estimate. The vertical "0 MMT CO_2e" line represents the mean emissions estimate for each category because all uncertainty occurs around the mean. The "CO_2", "N_2O", "CH_4", and "PFC, HFC, SF_6, NF_3" categories indicate total uncertainty of the emissions of each gas from the combined energy, industrial, agriculture, and waste sectors. "LULUCF" bar represents the uncertainty of net CO_2 sequestered from land use, land use change, and forestry. Percentage contribution to total inventory uncertainty is determined through error propagation, using 95 percent error bars as reported in NGHGI (2019) and assuming normal distributions and independence across all gases/sectors for simplicity of analysis. Under these assumptions, the LULUCF sector comprises nearly three quarters (70 percent) of total GHG inventory uncertainty. Note that in Figure 1, LULUCF includes only elements in Chapter 6 of the NGHGI, while the scope of this report includes all of Chapter 6 and some elements of Chapter 5 (see Table 1).



Percentages at end of bars represent the one-direction error bar divided by the mean.

5. These LULUCF CO_2 removal rates are based on NGHGI reported values since 1990 (2019).

GHG inventory uncertainty can create climate policy risk. Policy makers may be hesitant to set ambitious emissions reduction targets because they worry shifts in LULUCF GHG estimates could make achieving policy goals more difficult. This uncertainty could undermine confidence in U.S. GHG reporting. Without high-quality data on where and how land-based GHG emissions are occurring, the drivers of those emissions, and potential future changes in the LULUCF sector, policy makers may be hesitant to commit to ambitious climate targets. Addressing this policy risk is especially important as the United States and other countries set post-2025 targets under the UN Paris Agreement. Reducing the uncertainty associated with LULUCF emissions and projections will allow for more confident and ambitious planning, and improve the ability of U.S. government agencies to set and track progress towards climate targets over time.

The scope of this project covers the entire LULUCF chapter of the NGHGI (Chapter 6) as well as soil management sections of the Agriculture chapter (Chapter 5) *(see Table 1)*. This report refers to these categories collectively as LULUCF, although technically it is slightly broader than the Intergovernmental Panel on Climate Change (IPCC) definition of LULUCF and the elements in the NGHGI LULUCF chapter.

Table 1: Project scope

Shaded cells are from the Agriculture chapter of the NGHGI (Chapter 5). The rest of the cells are from the LULUCF chapter (Chapter 6) (NGHGI 2019).

	CO_2	CH_4	N_2O
Forest	· Biomass · Mineral and organic soils · Litter · Dead wood · Harvested wood products	· Forest fires · Drained organic soil	· Forest fires · Drained organic soil
Cropland, Grassland	· Mineral and organic soils	· Grassland fires · Drained organic soil	· Grassland fires · Drained organic soil
	· Mineral and organic soils	· Rice cultivation	· Agricultural soil management
Settlement	· Urban trees · Landfilled yard trimmings and food scraps · Organic soils	· Drained organic soil	· Drained organic soil · Synthetic N, biosolid application
Wetland	· Peat consumption · Mineral and organic soils	· Peat consumption · Mineral and organic soils	· Peat consumption · Mineral and organic soils

Over the past decade, the U.S. federal government has made real progress in improving the LULUCF GHG inventory. In December 2015, the White House released a report summarizing the federal government's LULUCF GHG inventory and projection improvements, which included better integration of data across agencies, updated forest carbon accounting methods, and expanded plot survey data (White House 2015).

Building on these important investments, this report identifies priority areas for continuing to reduce uncertainty and increase accuracy of the NGHGI. By identifying the largest sources of uncertainty and omitted fluxes, federal experts can target issues that will support the largest improvements, optimizing the use of staff time and budgets.

Common terms and references used throughout the document include:

– National Greenhouse Gas Inventory (NGHGI): The quantitative analysis in this report is primarily based on the NGHGI published in 2018, cited inline as "NGHGI 2018," which covers the inventory years 1990 to 2016. Although a more recent inventory, the 2019 NGHGI, is available, we focused on the 2018 NGHGI for our quantitative analysis because for the majority of our project it was the most complete inventory available. For purposes of our quantitative analysis, we note any significant methodological updates in the 2019 NGHGI. We reference the 2019 NGHGI in introductory and framing sections.

– IPCC (2006) guidance: The IPCC is a UN institution that synthesizes and disseminates global research findings on climate change. It has developed guidance for implementing national GHG inventories, and this guidance is the primary framework by which the international community judges inventory quality and completeness. IPCC (2006) is the most recent complete set of GHG inventory guidance used in the U.S. NGHGI, with a supplemental update in IPCC (2014) for wetlands. In May 2019, the IPCC released the "2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories," which is an additional source of guidance going forward.

– Tier 1, 2, and 3: These are IPCC methodologies for estimating national GHG emissions by source and sink categories. Tier 3 is the most rigorous and complex, often utilizing sophisticated models and country-specific datasets. Tiers 1 and 2 are followed when the detailed data and models of Tier 3 are not available—in these cases, simple equations using emission factors, land area, and activity data are used. In Tier 2, country-specific values are used while in Tier 1 IPCC default values are used.

– GHG flux: The land sector is somewhat unique among economic sectors in that GHGs can be both sequestered and emitted (except for small amounts of carbon capture and storage in the energy and industrial sectors). Therefore, the term "GHG emissions" is not always broad enough in the LULUCF context. We use the term "GHG flux" to refer collectively to both GHG emissions and CO_2 sequestered. A flux is simply a flow (here, of greenhouse gases) from one system to another (from plants, trees, and soil to the atmosphere, and vice versa).

– Carbon stock: This refers to the total amount of carbon stored in a given carbon pool and ecosystem type at a given point in time. Many LULUCF GHG flux categories estimate changes in carbon stock over time to estimate net CO_2 emitted or sequestered.

– 95 percent confidence interval: This is a statistical concept that measures the uncertainty of an estimate. In this report a 95 percent confidence interval is a range of values that we are 95 percent certain contains the true GHG flux value we are estimating, conditional on a number of assumptions. It is one of the primary tools used in our uncertainty attribution analysis, described further in the next section.

– Standard deviation and variance: These are two closely related statistical concepts that are also measurements of uncertainty. Variance is the average squared difference between each sample point and the average of all sample points. Standard deviation is the square root of variance. For a sample of data points with a normal distribution, the 95 percent confidence interval in one direction away from the mean is the standard deviation multiplied by 1.96. Thus we can see how all these uncertainty concepts are related and at times used interchangeably in the text below.

For the remainder of this report, we provide information on our analytical framework, our methods, and our results. Section 2 provides background on estimating uncertainty and accuracy, and how this informs our methods. Sections 3, 4, 5, and 6 provide uncertainty and omitted flux results for Forests, Cropland/Grassland, Settlements, and Wetlands respectively, along with recommendations for addressing the largest sources of uncertainty and omitted GHG fluxes. Section 7 estimates omitted fluxes in Alaska, Hawaii, and Puerto Rico. Section 8 describes our "blue sky vision" for a nationally consistent GHG inventory system for the land sector.

Uncertainty and Accuracy in the Greenhouse Gas Inventory

In this section, we define "uncertainty" and "accuracy" and describe how our analysis will investigate these issues in order to develop recommendations for improving LULUCF GHG inventory methods.

Uncertainty and accuracy are two key factors that influence our confidence in NGHGI reported estimates:

– Uncertainty reflects how much potential variation there is around an estimated GHG flux, and thus how close the estimate might be to the true GHG flux value. There are many possible sources of uncertainty, but most relate to how much variation we find by sampling data points as inputs to a calculation. We are particularly interested in attributing uncertainty across different elements of each calculation in the NGHGI.

– Accuracy reflects whether the main reported estimate of a given GHG flux is centered correctly at the true value of that GHG flux. It is often difficult to measure accuracy because we don't know the true value (that's the whole point of estimation, to guess the true value!), but we can point to ways that accuracy might be affected, like missing entire categories of GHG fluxes that will bias the NGHGI estimates in one direction or another.

Accuracy and uncertainty are often represented most simply in a dartboard setting, as shown in Figure 2. In an ideal world, NGHGI estimates will exhibit both high accuracy and low uncertainty, but there is potential for both issues to create challenges when interpreting GHG flux estimates.

We give further examples of both concepts below and also explain how we address NGHGI accuracy and uncertainty in our analysis.

Figure 2: Accuracy vs. Uncertainty

IMPROVING NGHGI ACCURACY

Accuracy is often impacted by omitting whole categories of GHG fluxes. To assess these types of accuracy issues, we thoroughly reviewed the methods, input data, and models utilized in each section of the NGHGI and sought to identify all notable omitted fluxes. For each omitted flux identified, we performed a literature review to identify activity data and emission factors to estimate first-order or rough estimates of the omitted flux wherever possible. Omitted fluxes that we could not estimate due to lack of data are listed at the end of this section *(see Table 2)*.

Most of the omitted fluxes identified in this report are already recognized as omissions in the NGHGI and are slated as planned improvements for future inventories. We take this discussion one step further by prioritizing the omitted fluxes by (rough, estimated) magnitude. Some omitted fluxes we estimate include CO_2 sequestered in woody biomass on croplands and grasslands, N_2O emissions on federal cropland and grassland (excluding N_2O from pasture, rangeland, and paddock [PRP] manure), CO_2 emissions on urban mineral soils, and omitted fluxes in Alaska and Hawaii.

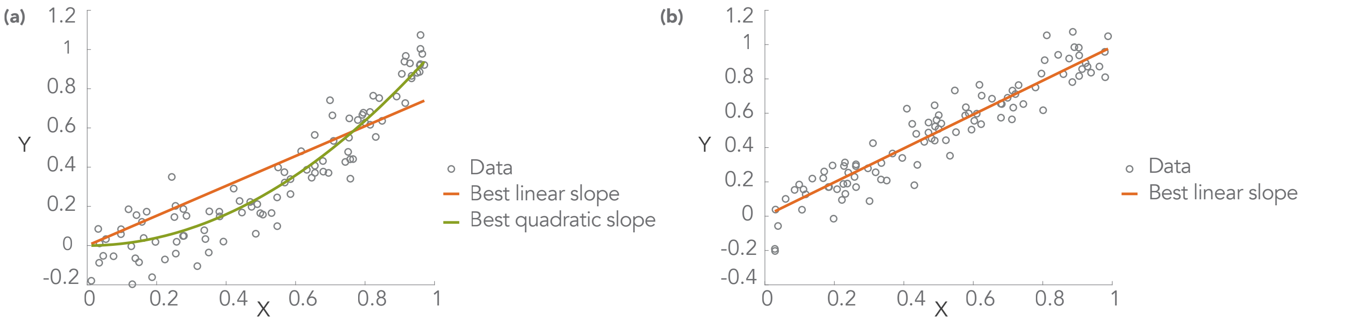
Accuracy issues can also result from misspecifying the model used to calculate the flux—in this context, not adequately capturing the true flux is generally referred to as "bias." Since one rarely, if ever, has true data points for GHG fluxes, it can be impossible to tell whether model misspecification has occurred, but it might be possible to say whether models are likely to over- or underestimate the true GHG flux. We try to note where over- or underestimation is likely in our analysis, but in general it is difficult to quantify bias from model misspecification, and therefore we do not attempt to do so.

Figure 3 shows a theoretical example of how model misspecification can bias GHG estimates. For example, assume X is an input to a model used to estimate Y, and suppose that the true relationship between X and Y is $Y = X^2 + \varepsilon$, where ε is a normal randomly distributed variable (just consider it a factor that randomly perturbs Y away from X^2; it is where our variation comes from). In panel (a) of Figure 3, using a linear model to estimate Y from X (the orange line), or assuming $Y = X$, would result in overestimating average Y for low values of X and underestimating average Y for high values of X. This is an example of model misspecification bias.

Conversely, now imagine we are in a world where the true relationship between Y and X is $Y = X + \varepsilon$. In Figure 3

Figure 3: Example of model misspecification and resulting bias

(a) Linear model is misspecified. True relationship: $Y = X^2 + \varepsilon$. (b) Linear model is well-specified. True relationship: $Y = X + \varepsilon$.



panel (b), we see that a linear model accurately estimates the average Y value for all values of X.

REDUCING NGHGI UNCERTAINTY

To understand how we can address uncertainty, it helps to understand the sources and types of uncertainty in GHG estimation, including scientific uncertainty, estimation uncertainty, measurement uncertainty, and sampling uncertainty.

– Scientific uncertainty: This type of uncertainty boils down to "we don't know what we don't know." We can reduce scientific uncertainty by investing in primary research and exploring how to improve methods and data collection. It is impossible, however, to quantitatively estimate how much scientific uncertainty is embedded in GHG flux calculations.

For example, soil carbon science is still evolving. Researchers are developing new models to capture the transformation of carbon inputs into different chemical and physical structures within the soil. New primary research and model development could change existing models for estimating soil carbon.

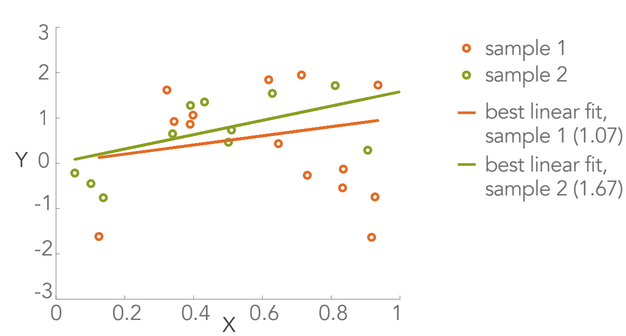
– Estimation uncertainty: Estimation uncertainty stems from the use of models, parameters, and data inputs to calculate a GHG flux and is the most commonly quantified source of uncertainty because there are statistical methods available to do so. Different types of models lend themselves to different strategies for calculating estimation uncertainty. Estimation uncertainty can be reduced by increasing the amount of data used to calculate model parameters, adjusting model specification, changing model structure, and other options.

For example, NGHGI Tier 1 or 2 equations are very simple and generally involve multiplying some activity data (e.g., land area in hectares) by an emission factor (e.g., grams CO_2e per hectare). Let's assume the emission factor is unbiased in this context (ignoring any accuracy issues described above)—there still exists uncertainty in how well the parameter reflects the true relationship between the activity data and total GHG flux due to the randomness by which the data used to calculate the emission factor is generated. Therefore, to calculate uncertainty from this model, we want to know the variance of the underlying data used to calculate the emission factor. IPCC (2006) guidance provides variance information for most emission factors for this reason.

Figure 4 shows how the randomness of the underlying data will influence the emission factor and thus highlights our motivation to calculate the uncertainty of the true emission factor. Here, the true relationship is $Y = X + \varepsilon$ (again, ε is a normal randomly distributed variable). Thus, the best model would find that, on average, we should multiply X by 1 to estimate Y. Suppose, however, we only have a sample of 15 data points, each one telling us total emissions generated over some land area. These 15 sample points are generated randomly from the model $Y = X + \varepsilon$. In the first sample (orange points), we find that the linear model would multiply X by 1.07 to find Y. In the second sample, the linear model would multiply X by 1.67 to find Y, a 67 percent overshoot of the real relationship. Thus, we can see that even though both samples are consistent with the same underlying relationship, the random sampling of data to generate model parameters can contribute significant uncertainty to GHG estimates.

Figure 4: Uncertainty of model parameters due to randomly sampling data points

$Y = X + \varepsilon$ is the true model, where ε is a standard normal random variable. Sample 1 and sample 2 each have 15 data points. Sample 1 results in model estimation of $Y = 1.07*X$. Sample 2 results in model estimation of $Y = 1.67*X$.



As an example of estimation uncertainty for a more complex model, Ogle et al. (2007) estimate the uncertainty generated by the soil GHG model DayCent by comparing model outputs to direct soil carbon and N_2O measurements *(see Figure A-12 in NGHGI 2019, Appendix 3)*. Even the most complex models cannot perfectly align with reality, which makes estimation error ubiquitous.

– Measurement uncertainty: Measurement uncertainty results from either human error in taking direct data measurements or systematic errors in measurement methods. Measurement error can be reduced by standardizing measurement methods across studies, researching accuracy and uncertainty of measurement methods, and continually monitoring measurements to catch errors.

Human error is easy to understand. Systematic errors in measurement methods can be more insidious. For example, soil organic carbon is difficult to measure directly, and there are concerns that the most popular chemical methods are too destructive and may not capture true soil carbon content (Stockmann et al. 2013).

– Sampling uncertainty: In some sections of the NGHGI, small-scale, plot-level carbon estimates are derived and then scaled up to estimate total carbon flux across a larger land area. A larger number of plots, or sample data points, can help reduce sampling error.

For example, to estimate forest carbon fluxes, the NGHGI uses measurements made at Forest Inventory and Analysis (FIA) plots that are randomly placed across the entire country. The carbon estimate for each plot is then multiplied by the land area it represents (e.g., across forested area with the same canopy cover and within the same state).

UNCERTAINTY ATTRIBUTION METHODS

Our main objective is to identify the sources of NGHGI uncertainty in order to assess where improvements in datasets, models, and analysis can be made. Specifically, we look at the uncertainty around each annual estimate of NGHGI LULUCF flux. Going forward we refer to this as the "annual uncertainty approach." Many previous studies have assessed NGHGI uncertainty, which helps focus our task on uncertainty attribution (NGHGI 2019; Ogel et al. 2010; Ogle et al. 2007; Ogle et al. 2003; Del Grosso et al. 2009; Domke et al. 2016; Jenkins et al. 2003; Jenkins et al. 2004; Skog 2008; Skog et al. 2004). This means we estimate the amount of uncertainty coming from each dataset, model, parameter, or other element of NGHGI calculations.

Our uncertainty attribution approach includes the following steps:

– We review every GHG flux calculation and, where possible, recreate the calculation using available data and models.

– For GHG fluxes where we can recreate the calculation methods used, we identify all inputs, parameters, and model components (collectively, elements) that have potential to contribute uncertainty to the final result and use literature review or assumptions to estimate the uncertainty of those elements. Then we estimate uncertainty attribution through a contribution index calculation *(see Equation 1 in the Technical Appendix; Ogle et al. 2003)*.

– For GHG fluxes where we cannot recreate the calculation method, we use uncertainty attribution results from literature or expert surveys to identify the largest sources of uncertainty.

– Uncertainty elements we could not quantify are listed in Table 2.

In our analysis, we focus on quantifying and attributing uncertainty from model specification and parameters, as well as uncertainty from sample to population extrapolation. We generally take direct data measurements and reported data as given (assuming no measurement error). Further, we generally assume that underlying models and methods are unbiased — that is, bias only enters the GHG flux estimates by omitting whole categories of GHG fluxes. Where data, models, or parameters have reported uncertainty or error bars, we include this information in our uncertainty analysis wherever possible.

Our results report the contribution of each uncertainty element to its respective GHG flux calculation's 95 percent confidence interval. This is a range defined by two end-point values, indicating that we can be 95 percent certain that the values within this range include the true GHG flux we are trying to estimate. We are able to convert all uncertainty attribution results into MMT CO_2e by multiplying each uncertainty element's attribution percentage by the magnitude of the GHG flux 95 percent confidence interval. This allows for comparing uncertainty elements across all calculations and all GHG flux categories in the NGHGI. It is not, however, valid to add together all the uncertainty attribution values to get total uncertainty of the NGHGI. First, not all of the uncertainty attribution results will be independent. Second, the 95 percent confidence values first must be converted into variance (the average squared difference between each sample point and the average of all sample points), which, assuming independence, could be added across all categories. It is not the objective of our study to recalculate total uncertainty of the LULUCF NGHGI but rather to attribute sources of uncertainty.

We do not quantify the potential for reduction in uncertainty that could be gained from each recommendation as this is outside the scope of our project. We assume the potential for uncertainty reduction from each recommendation is proportional to the amount of uncertainty contributed from all the elements to which it is relevant. Further research could usefully quantify the gains in accuracy and uncertainty through each recommendation.

TREND UNCERTAINTY AND INTERANNUAL VARIATION

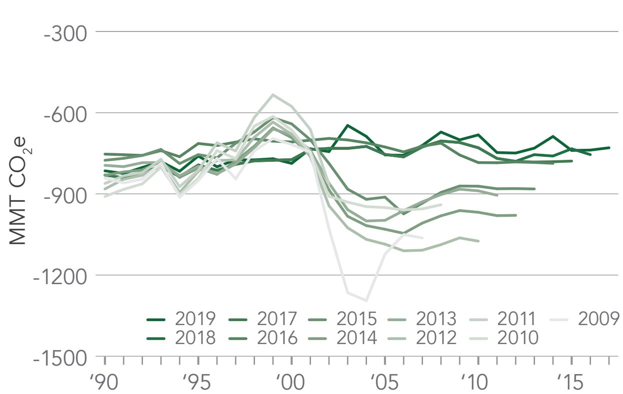
There are other approaches for thinking about NGHGI uncertainty rather than the annual uncertainty approach we focus on in this report. For example, the NGHGI also reports trend uncertainty by using Monte Carlo analysis (many random draws) for both the base year 1990 and the current inventory year, assuming both years have the same proportional error bars on their annual GHG estimates, and calculate the percent change in GHG flux between the two years for all the random draws. Because this calculation depends on annual GHG flux uncertainty (which is what we assess in this report), the trend uncertainty is similar in magnitude to the annual uncertainty, with 2017 trend uncertainty for LULUCF GHG flux levels reported as -51 percent to 62 percent change from 1990 LULUCF GHG flux levels (NGHGI 2019). That is, we have 95 percent confidence that LULUCF emissions may have decreased by as much as 51 percent or increased by as much as 62 percent since 1990. Addressing annual uncertainty values will also help to reduce trend uncertainty.

One could also look only at the interannual variation in NGHGI LULUCF fluxes, treating each of the total LULUCF GHG estimates since 1990 as a single observation, taking the average of all the observations, and finding the variance of all observations around this average. This would result in estimating lower uncertainty in LULUCF GHG fluxes because the variation of the reported NGHGI LULUCF flux over time is lower than the total annual uncertainty of the NGHGI LULUCF flux.

Using interannual variation to measure NGHGI uncertainty might not be appropriate since we know there is large uncertainty in each annual estimate. Additionally, adjustments to NGHGI LULUCF methods over time have resulted in variation in the LULUCF GHG time series as a whole, underlining the concern that NGHGI uncertainty cannot be fully reflected in interannual variation *(see Figure 5)*. We posit that improving the accuracy and reducing annual uncertainty of the LULUCF GHG inventory can help reduce this fluctuation over time.

Figure 5: Variation in NGHGI LULUCF estimates across publication years (Ohrel in press)

Each line represents the reported NGHGI LULUCF time series (carbon stock change only) for publication years 2009 to 2019. Changes in the time series are due to changes in methods and included categories.



UNQUANTIFIED UNCERTAINTIES AND OMITTED FLUXES

There are a number of sources of uncertainty and omitted fluxes that we were not able to investigate due to lack of information or did not calculate due to complexity of the estimation process. We summarize these elements in Table 2. Most of these elements are discussed in more detail in the Technical Appendix.

We were unable to calculate a number of uncertainties due to land use conversions and land use representation. The difficulty in accounting for uncertainty from these elements stems from the use of multiple datasets and models and a lack of access to the full datasets and methods. Some of these omitted fluxes could be sizable, including omission of all inland wetland GHG fluxes and the lack of accounting for non-soil carbon stock changes for many land conversions. Total uncertainty of land use representation is likely to be sizable as well, given that remote sensing imagery-based datasets like NLCD can have 80 to 90 percent overall accuracy (Wickham et al. 2017). The NGHGI would usefully report total uncertainty from land use representation to address this gap.

RECOMMENDATIONS FOR BETTER UNDERSTANDING AND REPORTING NGHGI UNCERTAINTY

We have several recommendations that would help reviewers, researchers, and policy makers understand uncertainty and accuracy in the NGHGI, and support future efforts to continually improve NGHGI estimates:

- Report exactly what is and is not included in estimating uncertainty for each GHG flux;
- Report specific uncertainty calculation methods such that they are replicable; and
- Make raw data readily available for all NGHGI calculations to better enable replication of inventory methods.

For example, some LULUCF GHG flux estimates use autoregressive-moving-average (ARMA) regressions to extend estimates from past years to the current inventory year, but do not report the regression model form or ancillary input data used. Tier 1 and 2 calculations for cropland and grassland are also not replicable (an issue we discuss at length in the Technical Appendix) due to incomplete reporting on activity data, which is constrained by NRI confidentiality.

These are best practices and allow for continued improvement of methods as well as an enhanced ability to compare and apply NGHGI results and methods to other studies.

Table 2: Identified uncertainties and omitted fluxes not quantified in this report

Sector	Uncertainty or Omitted flux	Element
Forests	Omitted flux	Mineralized N_2O from forest soil
Forests	Omitted flux	When forest land shifts from *Land Converted to Forest to Forest Remaining Forest* after 20 years, soil carbon calculation switches from Tier 2 to Tier 3 method
Forests	Omitted flux, Uncertainty	Assumption that 50% of forest carbon is lost in conversion of forests to grasslands in Western and Great Plains states
Forests	Uncertainty	Forest population stratification method is different by state, and the method itself (via remote imagery interpretation) contributes uncertainty
Forests	Uncertainty	Use of empirical forest age transition matrices
Forests	Uncertainty	Use of theoretical forest transition matrices in Western U.S. compared to empirical transition matrices in Eastern U.S.
Forests	Uncertainty	Modeling error for land conversions involving forests
Forests	Uncertainty	Error associated with estimation of downed dead wood and understory carbon stock change
Forests	Uncertainty	Sample error associated with litter and soil carbon stocks
Cropland/ Grassland	Omitted flux	Carbon stock change due to biochar application (initial methods provided in 2019 IPCC guidance)
Settlements	Uncertainty	Use of reference C stocks for cultivated mineral cropland across all *Land Converted to Settlement*
Settlements	Omitted flux, Uncertainty	Use of cropland emission factor for drained organic soil on *Land Converted to Settlement*, and assume 70% soil carbon loss
Settlements	Omitted flux	Non-CO_2 from wildfire
Wetlands	Omitted flux	GHG fluxes on inland (non-coastal) wetlands
Wetlands	Omitted flux	*Land Converted to Wetland* category does not include land converted to inland wetland
Wetlands	Omitted flux	*Land Converted to Wetland* does not include carbon stock changes due to biomass loss
Wetlands	Omitted flux	CH_4 from reservoirs, flooded lands, and agricultural ponds, canals, and ditches; work is ongoing at federal agencies to include this in the NGHGI and methods are included in 2019 IPCC guidance
Wetlands	Omitted flux	Carbon stock changes in seagrass beds; work is ongoing at federal agencies to include this in the NGHGI
Multiple	Uncertainty	Error on Global Warming Potential (GWP) values
Multiple	Uncertainty	Land use histories derived from NRI, NLCD, and FIA may underestimate land conversions before 1998 (but this is no longer an issues for future years). NRI and NLCD are not annually updated and can have lags and gaps in land use histories
Multiple	Uncertainty	Effect of harmonization of land use/land cover datasets (NLCD, NRI, FIA) for generating land base representation
Multiple	Uncertainty	Total uncertainty of land use representation as a factor across GHG flux calculations
Multiple	Omitted flux	No biomass, dead wood, litter carbon stock changes assumed for any land conversions other than to/from forest (except conversion to vegetated wetlands)
Multiple	Omitted flux, Uncertainty	Inconsistent Tier 3 soil carbon stock estimation methods for *Forest Converted to Cropland/Grassland*
Multiple	Uncertainty	*Land Converted to/from Cropland/Grassland* use of IPCC biomass carbon stock default for conversion
Multiple	Uncertainty	Measurement error

Forests

GHG FLUXES

The LULUCF NGHGI section on forests estimates GHG fluxes from the following categories:

- CO_2 fluxes from forest ecosystem carbon pools, including aboveground biomass of living trees, belowground biomass of living trees, dead wood, litter, and soils;
- CO_2 fluxes from harvested wood products in use and in waste disposal sites;
- CH_4 and N_2O fluxes from forest fires;
- N_2O fluxes from N additions to forest soils; and
- CO_2, CH_4, and N_2O fluxes from drained organic forest soils.

We have analyzed the sources of uncertainty associated with the estimation of each of these fluxes and use the results to prioritize actions to reduce uncertainty in this sector.

METHODS

Changes in forest carbon stocks account for the largest net CO_2 flux in the LULUCF GHG inventory. The NGHGI estimates the carbon stock change for forest ecosystem carbon pools using a suite of empirical and statistical models and using tree, litter, and soil measurements taken on field plots through the Forest Inventory and Analysis (FIA) program. Our methods to investigate forest carbon uncertainty benefited from extensive documentation on NGHGI forest carbon methods and FIA data transparency. This allowed us to perform more detailed analysis for this land category and develop more detailed recommendations than for other sections of this report.

For aboveground and belowground biomass of living and standing dead trees on *Forest Remaining Forest*, we re-created the carbon model applied to FIA measurements used at the national scale in the NGHGI (2018), applying some modifications for computational efficiency, and used this model to assess carbon fluxes in eastern Texas. We focus on a single U.S. region to minimize computational burden. We find that eastern Texas suitably represents national forest carbon uncertainty for several reasons. First, we find that the average annual sequestration rate in eastern Texas is 1.11 metric tons CO_2 per hectare, which is similar to the average annual national sequestration rate (1.44 metric tons CO_2 per ha, NGHGI 2018).[6] Second, we find that the 95 percent confidence interval as a percentage of mean sequestration for eastern Texas, including model and sample errors for aboveground and belowground living and standing dead biomass plus model error for litter and soil carbon stock changes (53.3 percent), compares well to that reported by the NGHGI (2018) for carbon stock changes in forest ecosystems in the entire United States in 2016 (43.2 percent).

The mix of tree species used in this analysis, and therefore the parameter uncertainty assessed here, is specific to eastern Texas and may not be representative of parameter uncertainty averaged over all U.S. forests, which has the potential to bias the estimated uncertainty results. Our primary objective, however, is to rank sources of uncertainty. As we will show below, the ranking results are both pronounced and intuitive given their roles in the carbon calculations. Therefore, we posit that the rankings generated from the eastern Texas analysis are sufficiently representative of what could be achieved through national analysis.

Using a Monte Carlo framework, we estimate the contributions to total uncertainty from: sampling (i.e., error associated with extrapolating data from ground plots to the total forest area) and nine groups of modeling parameters, each of which is described in detail in the Technical Appendix. Sampling error is by far the largest source of uncertainty. Two of the modeling parameters (those associated with the estimation of tree trunk biomass from tree diameter and height measurements) dominate the uncertainty contribution from model error. To estimate the national 95 percent confidence interval for carbon stock changes for aboveground and belowground living and standing dead biomass, we find the 95 percent confidence interval values for eastern Texas as a percentage of the mean sequestration value for eastern Texas, then multiply the percentages by the 2016 national mean carbon stock change as reported by the NGHGI (2018).

Our sampling error calculation method for eastern Texas may diverge from the national sampling error for two reasons: eastern Texas uses NLCD (2011) data for stratification by canopy cover, but, as we discuss below, other regions might use other data products or stratification approaches, making it difficult to identify one representative region for calculating sampling error; and we use a slightly different equation for calculating sampling error (Ogle et al. 2010) than what is used in the NGHGI (Bechtold and Patterson 2005), because the Ogle et al. (2010) approach allows us to utilize Monte Carlo results in estimating sampling error. We posit that these

6. Both eastern Texas and national values reflect net carbon sequestration only on *Forest Remaining Forest*. The national value includes downed dead wood and understory vegetation, which we do not include in our analysis for eastern Texas due to lack of time and because these are comparatively smaller biomass carbon pools.

differences would not impact overall ranking of uncertainty elements. Given the similarity in overall uncertainty between eastern Texas (53.3 percent) and national results (43.2 percent), we further posit that our sampling error estimate is within reason, but it is difficult to say whether eastern Texas sampling error over- or underestimates national sampling uncertainty.

For the litter and soil carbon pools, we estimate modeling error using separate Monte Carlo analyses that are based on reported summary data of carbon stocks (Domke et al. 2016; Domke et al. 2017). The magnitude of the modeling uncertainties that we calculate for carbon fluxes associated with the litter and soil carbon pools depend strongly on the assumptions that we apply in our estimation technique, as we describe in detail in the Technical Appendix. This might be one reason why our 95 percent confidence interval for eastern Texas (53.3 percent) is higher than the national 95 percent confidence interval (43.2 percent).

We run a fourth Monte Carlo analysis to estimate contributions to uncertainty associated with the input data and modeling parameters used to estimate CH_4 and N_2O emissions from forest fires. Uncertainty estimates associated with: N_2O fluxes from N additions to forest soils, and GHG fluxes from drained organic forest soils, are taken directly from NGHGI reported values.

To attribute uncertainty among the input data and modeling parameters used for estimation of GHG fluxes from harvested wood products, we use the published results of contribution index analyses (Skog 2008; Skog et al. 2004).

TOPLINE RESULTS

Table 3 lists the elements contributing the most uncertainty to the estimation of GHG fluxes in the forest sector. The Technical Appendix provides the complete results of our uncertainty analysis for this sector and also provides additional details of our estimation methods. The largest contributor to uncertainty is the sampling error estimated for forest tree biomass (434.3 MMT CO_2e). Other leading sources of uncertainty from the forest tree biomass category are two groups of modeling parameters, cumulatively accounting for an uncertainty contribution of 131.9 MMT CO_2e. Three of the uncertainty elements are associated with the input data and modeling parameters used for the estimation of CH_4 and N_2O fluxes from forest fires, accounting for a total uncertainty contribution of 38.5 MMT CO_2e. The remaining four uncertainty elements are associated with the input data and modeling parameters used for the estimation of CO_2 fluxes from harvested wood products, accounting for a total uncertainty contribution of 29.3 MMT CO_2e.

We recognize that the choice of analytical framework may have some impact on the ranking of the modeling parameters. For example, the uncertainty contribution estimated for the volume coefficients may be affected by the number of volume coefficients that are used in the calculation and that are therefore allowed to vary simultaneously in the Monte Carlo framework. We discuss this matter in the Technical Appendix and conclude that such impacts are not necessarily artifacts of the calculation itself but are valid reasons to focus efforts on reducing uncertainty for parameter groups with a large number of values.

RECOMMENDATIONS

1. **Increase field plot intensity and use remote sensing data to decrease sampling error:**

   Forest carbon sampling error represents the largest source of uncertainty in the entire LULUCF NGHGI, accounting for over 30 percent of total uncertainty attribution results across all land types. One way to reduce sampling error is to increase plot sampling. FIA has permanent sample plots located approximately every 2,428 hectares, but every plot is only sampled once every 5 to 10 years (plots in the eastern United States are sampled more frequently than in the west). Increasing the sampling rate of existing plots would be one way to reduce LULUCF uncertainty within the existing FIA program.

   While we did not estimate the uncertainty associated with the use of the age transition matrices that are used to project plot carbon stocks between re-measurements *(see Table 2)*, increasing the sampling rate would also reduce this uncertainty.

   Another option for reducing sampling uncertainty is to increase forest stratification so that individual plots are more closely related to the forest population area that they are meant to represent. For example, the forest stratification in eastern Texas is based on three regions (National Forest Service land, Northeast Texas, Southeast Texas), with each region divided into 2 to 4 bins of canopy cover. To reduce sampling error, regions could be divided into more canopy cover bins, which would result in a lower variance of carbon for plots included in each bin.

   Remote sensing data can play an important role in both improved forest stratification (discussed in the next recommendation) and in creating more plot level data to reduce sampling error. Satellite imagery and LiDAR data can be used to estimate aboveground biomass at FIA plots or over larger areas (Blackard et al. 2008; Lu et al. 2016; McRoberts et al. 2016; Ma et al. 2018). Some additional uncertainty would be introduced through this method but could be an improvement over sampling uncertainty. It could also result in cost reductions compared to additional on-the-ground measurements.

2. **Regularly update data to stratify and extrapolate forest plot data:**

   While we did not estimate the uncertainty from the NGHGI's forest stratification approach *(see Table 2)*, we did have concerns while performing our analysis that this factor might affect our results. Stratification of the U.S. forest population is undertaken so that each FIA forest plot represents a unique subset of the total forest land area. As discussed above, U.S. forest is stratified into regions and canopy cover bins, and the stratum area is divided across its respective plots in proportion with each plot's area of forest. The stratification method may differ by state, and a more complex stratification approach may be used for some regions in the NGHGI.

For eastern Texas, the NLCD 2011 dataset is used for stratification by canopy cover, but other datasets may be applied in other regions. It is not clear how frequently the canopy cover data is updated. If, for example, only NLCD 2011 canopy cover data is used, then we may not be adequately tracking changes in U.S. forest disturbances, especially if there are changes in the rates of disturbance as a proportion of total forest population over time. For example, increases in disturbance rates like harvesting or natural disturbances since 2011 will not be captured. Even though individual plots could capture greater levels of disturbance, they would be scaled up to disturbance areas found in 2011. Especially if policies start to advocate the use of wood products and wood bioenergy to mitigate climate change, and if natural disturbances like wildfires, floods, and hurricanes increase as a result of climate change, carbon loss rates in U.S. forests could increase and not be captured in the inventory for long periods of time.

This could prove a sizable source of uncertainty because satellite imagery interpretation is characterized by relatively large uncertainty. For example, NLCD products have approximately 80 to 90 percent overall accuracy (Wickham et al. 2017), and NLCD is only updated every few years—the most recent NLCD product is based on 2011 data, with the 2016 product released in May 2019. NAIP products require at least 90 percent accuracy. In either case, there is uncertainty of the imagery data both over time and space.

To address these concerns, annually updated satellite data should be used for forest stratification.

3. **Implement targeted data collection of tree measurements (e.g., tree density, volume, and diameter) to decrease modeling error for forest ecosystems:**

Two of the top contributors to uncertainty for the forest sector are modeling parameters used in the estimation of tree biomass. In many cases, the underlying data has been sourced from research published many decades ago and for which the analysis and raw data is either unclear or no longer available. For example, the volume coefficients used in eastern Texas are based on Hann and Bare (1978) and Chojnacky (1988). In many cases, only summary statistics, rather than the complete original datasets, are available. For many parameters (e.g., specific gravity, which is the ratio of wood or bark density to the density of water), there is a lack of species-specific or region-specific data. Collection of tree parameters targeted to the needs of carbon models would contribute to a reduction in the uncertainty associated with this sector. Ideally, future measurements would prioritize random tree sampling across different sizes, ages, climates, and other variables. Jenkins et al. (2004) notes a lack of random and complete sampling as a limitation of previous studies. Future studies should provide full reporting of underlying data and standard errors of any parameters derived from that data.

Furthermore, tree density is likely to be influenced by climate change, affecting tree species in different ways (Clough et al. 2016). These changes over time require dedicated research programs to track changes in forests and key parameters like density across species and over time.

4. **Develop more region-specific modeling parameters (e.g., fuel availability, combustion factors, and emission factors) to decrease modeling error from forest fires:**

Three of the top contributors to uncertainty for the forest sector are inputs to the estimation of non-CO_2 emissions from forest fires. NGHGI (2018) uses: state-level fuel availabilities; a single invariant emission factor for each gas that corresponds to the broad category of "extra-tropical forest;" and a single invariant combustion factor for the conterminous United States that corresponds to a general "temperate" forest category. The development and use of parameters that are more specific to the local conditions would reduce uncertainty in this sector. The 2019 NGHGI has started to implement this recommendation because the updated calculation uses fuel availabilities based on ecological regions rather than values simply derived by state, and the updated calculation also applies combustion factors based on burn severity.

Table 3: Top contributors of uncertainty in estimating GHG fluxes in the forest sector [a,b]

(a) The estimated modeling uncertainties associated with litter and soil carbon fluxes are highly dependent on the assumptions used in our modeling framework (see Technical Appendix for more information); therefore, we include these uncertainty elements in the table for reference, but do not include them in Table ES-1. (b) We discuss further in the Cropland and Grassland section why it may not be appropriate to attribute all of the soil methane sink to human activity. The negative value indicates CO_2 sequestered.

Type	Uncertainty element	Description of uncertainty	Contribution to uncertainty/ Omitted flux (MMT CO_2e)
Uncertainty	Forest tree biomass: Sampling error	Error associated with extrapolating plot-level measurements to state or national level. Our methods allow estimation of the sampling error associated with only forest tree biomass on *Forest Remaining Forest* and not that associated with the litter or soil pools or that associated with land conversions involving forests.	434.3
Uncertainty	Forest soils: Modeling error [a]	Model error associated with estimating soil carbon flux on *Forest Remaining Forest.*	255.7
Uncertainty	Forest tree biomass: Volume coefficients	Error associated with the modeling parameters used to estimate total tree stem volume from measurements of tree height and diameter. These coefficients are species-specific where appropriate data is available.	77.7
Uncertainty	Forest tree biomass: Wood and bark specific gravities	Error associated with the modeling parameters used to convert tree stem volume to biomass. Species-specific values are derived from measurements; where data for a given species is not available, data for a similar species or species group is assigned.	54.2
Uncertainty	Forest litter: Modeling error [a]	Model error associated with estimating litter carbon flux on *Forest Remaining Forest.*	33.2
Uncertainty	Forest fires: Fuel availabilities	Error associated with the modeling parameters that define the mass of dry matter available for combustion per unit area in the conterminous United States.	28.7
Uncertainty	Harvested wood products: Solid wood products data	Error associated with the input data for solid wood products production.	11.5
Uncertainty	Harvested wood products: Solid wood products conversion to carbon	Error associated with the conversion factor applied in the estimation of carbon in solid wood products.	10.8
Uncertainty	Forest fires: Emission factors	Error associated with the modeling parameters that define the mass of CH_4 or N_2O gas that is emitted per mass of dry matter burned. Default factors from IPCC (2006) are applied.	6.0
Uncertainty	Harvested wood products: Paper data	Error associated with the input data for paper production.	3.8
Uncertainty	Forest fires: Combustion factor	Error associated with fraction of woody biomass combusted in a forest fire for conterminous United States.	3.7
Uncertainty	Harvested wood products: Paper conversion to carbon	Error associated with the conversion factor applied in the estimation of carbon in paper products.	3.2
Omitted flux	Soil methane sink (forests) [b]	Methane consumed by soil microbes, not currently accounted for in the NGHGI	-3.8

Cropland and Grassland

GHG FLUXES

The NGHGI cropland and grassland sections estimate soil carbon changes as well as CO_2, N_2O, and CH_4 emissions from agricultural management practices. In this section we assess sources of uncertainty covering all cropland and grassland GHG fluxes included in NGHGI Chapter 6: LULUCF and agricultural soil management from Chapter 5: Agriculture.[7] The analysis here includes *Cropland Remaining Cropland*, *Grassland Remaining Grassland*, and *Land Converted to Cropland or Grassland*. Cropland and grassland GHG flux categories include:

- Soils

  CO_2 sequestration or emissions from mineral and organic soils

  CO_2, CH_4, N_2O emissions from drained organic soils

- Agricultural management

  N_2O emissions from fertilizer application, other inputs, and natural processes

  CH_4 from rice cultivation

- CH_4 and N_2O emissions from grassland fires

We also provide initial estimates of omitted GHG fluxes:

- CO_2 sequestration in woody biomass and litter on cropland and grassland
- CH_4 and N_2O emissions from woody biomass in grassland fires
- Omitted CO_2 and N_2O emissions on federal cropland and grasslands
- CH_4 sequestration by soil microbes

Both the uncertainty analysis and missing category estimates are used to prioritize options for reducing uncertainty and addressing omitted fluxes in the NGHGI cropland and grassland sections.

METHODS

The majority of GHG soil carbon emissions and sequestration on mineral soils, as well as most agricultural N_2O and rice methane emissions are calculated with DayCent.[8] DayCent is a biogeochemical model that recreates the cycling of carbon and other nutrients in soils and plant material in order to estimate carbon storage and GHG emissions. For certain soil and land types the complex data inputs required by DayCent are not available, or DayCent has not been parameterized. In these cases the NGHGI follows Tier 1 and 2 methods using default IPCC equations, and, where possible, U.S.-specific data. Tier 1 and 2 is used for all organic soils, many federal cropland and grassland fluxes, and fire-related emissions. As discussed in the Introduction, Tier 1 and 2 methods have lower accuracy and higher uncertainty than Tier 3 methods.

Due to DayCent's complexity as well as the confidentiality of the primary data (National Resources Inventory - NRI), we were unable to replicate the Tier 3 calculations and perform uncertainty attribution analysis as we did in other sections of this report. As an alternative, we issued a survey to experts in soil science and carbon accounting across academia, government, the private sector, and non-profits. We asked them a series of prompts falling into two categories: Section 1 asked them to provide their best quantitative estimate of the percentage contribution to uncertainty of each element of the DayCent model and the input data; and Section 2 asked them to rank priority research needs for reducing uncertainty of soil and agricultural management GHG emissions estimates. The survey received a maximum of 19 responses for each prompt and a minimum of 5 responses.

For Tiers 1 and 2 we used uncertainty attribution results from existing literature because we were unable to replicate the calculations due to NRI confidentiality (Ogle et al. 2003).

To estimate omitted fluxes we used publicly available data and values found in the literature.

See the Technical Appendix for more details on the design and respondents of our expert survey along with complete survey results, the alternative methodology for Tiers 1 and 2, and omitted flux calculations and literature sources.

TOPLINE RESULTS

Table 4 highlights the largest elements contributing to cropland and grassland GHG uncertainty and omitted GHG fluxes. Table 5 shows the top ranked priorities for data and method improvements as identified in Section 2 of our expert survey, which asked experts to rank research, modeling, and data priorities for reducing GHG flux uncertainty from cropland and grassland soils and agricultural management. These priorities feature prominently in our recommendations.

7. We include the Chapter 5 categories because they use the same model and are subject to many similar uncertainty issues.
8. NGHGI cropland and grassland sections use Tier 3 DayCent model on 78 percent of the cropland and grassland area on which soil carbon stock changes are calculated, and over 90 percent of N_2O and rice methane emissions (NGHGI 2019, Annex 3.12).

RECOMMENDATIONS

While there are many ways to synthesize our results into policy recommendations, we identify some cross-cutting priorities to address the largest sources of uncertainty and omitted fluxes:

1. **Establish a greater number of diverse sites for gathering soil data, and make this data easily accessible to all:**

   Survey respondents noted that they were keen to have more, and better, empirical data, in order to improve and validate existing soil models. They acknowledged the difficulties in modeling such a complex system but noted that more data is the primary way to help reduce both input and structural uncertainty. For example, NRI plots could form the basis of a national soil carbon monitoring network, similar to FIA plots for forests. They also believed it is important to have more comprehensive and cohesive datasets, accessible to all. Some of these issues may be addressed through the introduction of the USDA Natural Resources Conservation Service's (NRCS) Conservation Effect Assessment Project (CEAP) into NGHGI analysis. CEAP is a subset of NRI points where extensive land use and land use management data has been collected, along with data on conservation activities. An imputation method has been developed to expand CEAP information to all NRI points for use in the NGHGI.

   Note that inaccessibility of the NRI dataset, in stark contrast to the FIA dataset, is a major stumbling block and should be addressed, whether by developing new datasets that are publicly available or making some portion of NRI data public. The NGHGI notes that USDA is developing a national soil monitoring network, but this work can and should be expedited with funding and political priority. It is one of the primary opportunities for improving NGHGI cropland and grassland estimates.

2. **Support collaboration across governmental and non-governmental soil science teams:**

   Given the complexities of modeling the soil system, survey respondents indicated that increased collaboration among model developers would help refine and improve soil carbon flux predictions. Increased inter-model comparison, model validation, and collaboration were highly ranked as opportunities to reduce uncertainty across the board. Even within the federal government, there exists little opportunity for experts working on soils for different parts of the LULUCF NGHGI to collaborate and develop common methods. This is particularly challenging for GHG fluxes from land use conversion, since different teams work on different land use types.

3. **Prioritize primary research on soil microbial communities and their interactions with carbon and nutrient cycling:**

   This was the highest ranked primary research priority and would provide an important opportunity to reduce DayCent structural uncertainty (organic matter formation; nitrification processes). In conversations with experts and in the literature, this is frequently cited as an issue that confounds predictions of how carbon moves through soils and how much carbon is stored over the long term. This research can also support estimates of the soil methane microbial sink, a potentially sizable GHG flux currently not accounted for in the NGHGI.

4. **Support additional research on the N cycle and soil N_2O measurements:**

   Experts indicated that there is still room to improve estimates of soil N_2O emissions as three of the top opportunities for reducing uncertainty. Additional experimental data, measurements, and reconciliation with atmospheric measurements of N_2O can all improve soil N_2O estimates. Nitrification and denitrification processes were ranked as the fourth largest source of structural uncertainty in DayCent, and N_2O emissions are the largest GHG flux from croplands and grasslands (266 MMT CO_2e), dwarfing all other soil and omitted fluxes.

5. **Estimate omitted fluxes in federal lands, cropland and grassland biomass and litter, and soil microbial methane fluxes:**

   These three categories of omitted fluxes could comprise a large share of carbon stock changes in croplands and grasslands. Resource and data constraints prevented their inclusion in past NGHGI reports, but given our first order estimates of fluxes, it should be a priority to estimate them going forward. Additional data and analysis is required to improve on our estimates, such as expanding the NRI program to federal lands and estimating woodland carbon fluxes using FIA data.

   We included the soil methane sink as a bulleted element in both the Forests and Cropland/Grassland top results lists because, while it is potentially a large flux, it is not clear how much of this sink can be attributed to human management. It is useful, however, to have a complete accounting of all GHG sources and sinks. NGHGI authors and policy makers can further determine how much of each flux should be tracked as part of U.S. emissions reduction goals. We discuss these issues further in the Technical Appendix.

Table 4: Top contributors to cropland and grassland uncertainty and omitted fluxes

(a) It may not be appropriate to attribute all of the soil methane sink to human activity.

Type	Uncertainty element	Description of uncertainty	Contribution to uncertainty (MMT CO_2e)
Uncertainty	Soil properties	Soil texture and natural drainage capacity are the primary soil variables used in NGHGI cropland/grassland soil carbon modeling, but data collection is coarse.	31.3
Uncertainty	Leaching, runoff, and volatilization	Variability in fertilizer and organic amendment create uncertainty, along with lack of data on indirect N_2O.	28.6
Uncertainty	Organic matter formation and decomposition	Soil carbon is only measured to 30 cm deep; a simplified model is used to represent carbon and nitrogen cycling.	25.6
Uncertainty	Nitrification and denitrification processes	Nitrification and denitrification are modeled based on unobservable soil characteristics, like pore space.	24.1
Uncertainty	Manure and other organic fertilizer applications	Land area of manure application is based on 1997 estimates, and accompanied by other simplifying assumptions.	23.4
Uncertainty	Tillage (conventional, reduced, no-till)	There is lack of data on tillage practice adoption, especially on continuous no-till; changes in tillage technologies and application rates create additional uncertainty.	23.4
Uncertainty	Fertilization management	Lack of activity data at smaller geographic scales creates challenges; specifics around N fertilization (e.g., amount of N applied to each crop type), are not always available.	21.9
Uncertainty	Soil and water temperature regimes	Soil and water temperature are DayCent inputs that govern carbon and nutrient cycling rates, and these dynamics are uncertain.	15.7
Omitted flux	Total federal land N_2O emissions (cropland and grassland) minus PRP	The majority of federal lands are not currently estimated in the NGHGI, due to resource constraints.	21.8
Omitted flux	Soil methane sink (cropland and grassland)[a]	The methane sink from soil microbes is not currently estimated in the NGHGI.	-21.3
Omitted flux	Woody biomass on grasslands	The NGHGI team has performed preliminary estimates of woody biomass on grasslands and plans to expand the calculations in the future.	-20.0

Table 5: Expert survey results—priorities for research, modeling, and data collection

Survey respondents were asked to rank proposed research needs in accordance with their ability to reduce uncertainty in estimating national GHG fluxes from croplands and grasslands, with 1 representing the least impactful and 5 representing the most impactful.

Category	Proposed research need	Average rating (1 min, 5 max)
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	4.27
Empirical data needs	Establish a national soil monitoring network to produce a full and consistent dataset of soil carbon measurements over time	4.27
Model development	Improve model validation with updated comparisons to empirical regression models that are based on field experiments	4.18
Model development	Increase collaboration among model developers, shifting to a community-centered, open-source approach and integrating databases and computational tools	4.09
Primary research	Influence of microbial activity—and other physicochemical and biological influences—on decomposition of organic matter/carbon, nitrogen and phosphorous cycling	4.00

Settlements

GHG FLUXES

The NGHGI settlements section estimates carbon sequestered and emitted from urban trees, drained organic soils, and yard trimmings and food scraps, as well as N_2O emissions from settlement soils. In this section we assess sources of uncertainty covering each of these fluxes:

- CO_2 sequestration or emissions from urban trees
- CO_2 emissions from drained organic soils
- N_2O emissions from fertilizer application and other inputs
- CO_2 sequestration or emissions from yard trimmings and food scraps in landfills[9]

Beyond examining currently estimated NGHGI fluxes, we also provide an initial estimate of carbon sequestered and emitted from settlement mineral soils, which is not currently accounted for in the NGHGI—the majority of settlement soils are mineral, not organic, so this is potentially a large omitted flux.[10]

METHODS

The largest settlement GHG flux is carbon sequestration in urban trees (technically, trees in any developed areas). Urban tree carbon flux is calculated at the state-level, requiring estimates of developed area tree cover and tree growth rates by state. To assess sources of uncertainty for these calculations, we ran a contribution index analysis for all components of the developed area tree carbon flux equation: urban area, percent tree cover, gross sequestration rate, and gross to net sequestration ratio. Each of these components come from data found in existing literature. For more information on the NGHGI urban tree calculation methods, see the Technical Appendix.

For settlement soils, the NGHGI reports N_2O emissions from all settlement soils and CO_2 emissions from drained organic soils. Uncertainty is estimated for both through Monte Carlo and error propagation methods. Due to the small scale of these fluxes, we do not break down uncertainty contribution beyond what is reported in the NGHGI.

Carbon stored and emitted by landfilled yard waste and food scraps is calculated in the NGHGI by estimating landfilled material back to 1960 and calculating the degradation of these organic materials over time. The calculation includes factors like percentage of total waste stream comprised of yard trimmings and food scraps, and breaking the organic waste stream into individual categories like grass vs. leaves vs. branches, and estimating moisture content, initial carbon content, and decay rates for each category. We use the contribution index approach to assess uncertainty from each of the elements in the yard trimmings and food scraps equation, using Monte Carlo simulations. For more information on these calculations, see the Technical Appendix.

Finally, we also estimate potential CO_2 fluxes from settlement mineral soils, which is omitted from the NGHGI due to lack of data. While omitting carbon flux from settlement mineral soils is consistent with IPCC (2006) guidance, we find in the literature that it has potential to be a large source of CO_2 emissions (Decina et al. 2016). We use IPCC Tier 2 methods to estimate mineral soil CO_2 fluxes assuming settlement soils are closest in management regime to low input cropland soils, based on available IPCC factors.[11] This results in a relatively high estimate, but lower than that derived from settlement-specific emission factors in Decina et al. (2016).

TOPLINE RESULTS

Table 6 highlights the largest elements contributing to settlement GHG uncertainty and the omitted mineral soil GHG flux. For a more detailed discussion and complete presentation of our survey results and omitted flux calculations, see the Technical Appendix.

Urban tree elements dwarf the yard trimmings and food scraps elements, and the omission of mineral soils is sizable. The largest contributor to uncertainty by far is the "gross to net sequestration ratio" used to estimate how much net carbon is gained in urban trees annually.

9. Although other waste components are considered in *NGHGI Chapter 7: Waste*, yard trimmings and food scraps are considered part of the settlements component of the LULUCF chapter because most of the yard trimmings originate from urban areas, and because landfills are managed primarily on settled areas.
10. We do not account for undrained settlement organic soils because all organic soils in settlement areas are assumed to be drained, a reasonable assumption according to IPCC (2006).
11. As with other omitted flux estimates in this report, this is only a first order estimate. We do not believe that settlement soils are managed the same as low input cropland soils, but we posit this estimate might have the right order of magnitude.

RECOMMENDATIONS

1. **Align urban tree carbon estimation methods with NGHGI forestry methods:**

   Carbon stock estimates from trees are also estimated in the NGHGI forestry section, but urban trees are calculated differently using a separate methodology particular to urban areas. This necessitates developing factors like the "gross to net sequestration ratio," the largest contributor to settlement uncertainty. Harmonizing the methods between the urban trees and forest section could help to reduce uncertainty.

2. **Estimate carbon fluxes on settlement mineral soils:**

   CO_2 fluxes on urban mineral soils are not estimated in the NGHGI, yet our initial calculations show they could comprise a large share of settlement GHG fluxes (35 MMT CO_2e). Right now there is limited data availability on settlement mineral soil carbon changes. More direct measurements in a variety of U.S. settlement areas would address this gap.

3. **Derive state-specific values for urban trees through additional plot data and satellite data analysis:**

   If the urban trees calculation remains largely the same, deriving state-specific values for gross sequestration and gross-to-net sequestration ratios will reduce uncertainty. Additional plot-level sampling is necessary to estimate state-level values, and high-resolution satellite data could help extrapolate plot values to similar regions. Regularly updated satellite data analysis would also help update estimates of percentage of settlement area covered by trees, another large source of uncertainty, which is currently limited by long lag times between NLCD updates.

4. **Improve organic waste data collection:**

   The largest source of uncertainty from yard waste and food scraps is the assumption of the percent food waste comprises of total organic waste. To address this uncertainty, new measurements would estimate the contribution of leaves, branches, grass, and food scraps to the overall waste volume. Furthermore, collecting and reporting these data annually could improve the quality of these calculations.

Table 6: Top contributors to settlement uncertainty and omitted fluxes

Type	Uncertainty element	Description of uncertainty	Contribution to uncertainty (MMT CO_2e)
Uncertainty	Urban trees gross to net sequestration ratio	Within the urban trees calculation, this value estimates the amount of sequestered carbon that is lost to downed branches or tree decay. There is a shortage of state-specific ratios, so a national value is used in most state-level calculations, introducing a large amount of uncertainty into the urban trees calculation.	86.5
Uncertainty	Urban trees gross sequestration rate	In the urban trees calculation, this value estimates the amount of carbon per area that is sequestered by trees. It is derived at the state-level from literature.	7.0
Uncertainty	Urban/Developed land area	In the urban trees calculation, this is the amount of land area on which urban/developed area trees are considered. Urban area was previously determined using Census determinations; the latest NGHGI uses the NLCD. Uncertainty is determined by expert opinion.	6.5
Uncertainty	Food scraps multiplier	In the yard trimmings and food scraps calculation, this is the ratio of total organic waste assumed to be food scraps. Since it is held constant throughout the time series, it introduces uncertainty.	5.8
Uncertainty	Urban tree cover percentage	The percentage of urban/developed land that has trees on it is derived at the state-level and is embedded with uncertainty due to satellite imagery interpretation.	4.3
Uncertainty	Percent of carbon stored in organic waste	In the yard trimmings and food scraps calculation, this is the amount of carbon stored when different types of organic waste decompose. They are held constant throughout the time series, and both the values and uncertainty are derived from literature.	3.6
Uncertainty	Moisture content of organic waste	In the yard trimmings and food scraps calculation, this is the percentage of different types of organic waste that is water. It is held constant throughout the time series, and both the values and uncertainty are derived from literature.	1.6
Uncertainty	Yard trimmings multiplier	In the yard trimmings and food scraps calculation, these ratios are used to determine the composition yard trimming waste from total biological waste. They are held constant throughout the time series, and uncertainty is based on expert judgement.	1.5
Uncertainty	Direct N_2O emissions from N additions to soils	Fertilizer applications on settlement soils result in N_2O emissions. Uncertainty comes from N input data, NRI data, default IPCC emission factors, and surrogate data extrapolation.	1.3
Omitted flux	CO_2 emissions from settlement mineral soils	Mineral soil flux is not calculated as part of the NGHGI, citing a lack of available data.	34.7

Wetlands

GHG FLUXES

The NGHGI wetlands section includes GHG flux estimates of:

- CO_2 and CH_4 emissions from coastal wetland soils
- N_2O from aquaculture
- CO_2, N_2O, and CH_4 emissions from managed peatlands

The IPCC defines wetlands as areas where the water table is artificially changed or created through human activity and does not fall into Forest, Cropland, or Grassland categories (IPCC 2014). The NGHGI indicates there are 43 million hectares of wetlands in the United States. Only 2.9 million hectares of coastal wetlands are included in GHG flux accounting. This gap is largely due to being unable to reliably designate U.S. inland wetlands as "managed" vs. "unmanaged." IPCC guidance requires that nations account for all anthropogenic GHG fluxes in their inventories. In the land sector, the distinction between anthropogenic and non-anthropogenic fluxes can be difficult if not impossible to make. Thus, the United States uses the "managed land proxy" to determine which land-related emissions should be included in the NGHGI—that is, all fluxes that occur on managed land should be accounted for. In U.S. land base estimates, all 43 million hectares of wetlands are labeled as managed, but this is only due to the inability to determine which wetlands are unmanaged. Furthermore, there are no U.S. datasets dedicated to tracking inland wetlands. We do, however, have coastal wetland data through the National Oceanographic and Atmospheric Administration (NOAA) Coastal Change Analysis Program (C-CAP). As a result, only coastal wetlands are accounted for in the NGHGI. There are over 40 million hectares of wetlands not accounted for, including 13 million hectares of inland and coastal wetlands in Alaska and Hawaii, with the remainder comprised of inland wetlands in the conterminous United States.

Work is underway to include flooded lands and reservoirs in future iterations of the NGHGI, using U.S.-specific methods and data. This will address some part of the 40 million hectares of currently omitted wetlands. Work is also underway to include carbon stock changes in seagrasses, a category not currently included in the NGHGI.

METHODS

Coastal wetland GHG emissions represent 0.5 percent of the total land-based NGHGI, largely due to the fact that they represent only 0.3 percent of total U.S. land area. Given its small contribution to total emissions, we present only a short synthesis of the wetland methods and uncertainty values. We did not further analyze sources of uncertainty beyond what is reported in the NGHGI. For additional detail on NGHGI wetland calculations, see the Technical Appendix.

Due to lack of data on the managed vs. unmanaged distinction and inland wetland characteristics we did not attempt to estimate the omitted flux from inland wetlands. This omission could be sizable given that the omitted area is approximately 4 percent of the managed U.S. land base. The scale of the omitted GHG flux will be determined largely by how much of U.S. wetlands are ultimately considered managed. We provide some additional wetlands estimates in the Alaska, Hawaii, and U.S. Territories section.

RESULTS

Table 7 shows the largest source of wetland uncertainty comes from estimating soil carbon stock change, which is calculated using emission factors from the literature. Furthermore, *Land Converted to Wetland* does not consider consistency of soil carbon methods across land use types, which will create inconsistent estimates of soil carbon fluxes for land use change to and from coastal wetlands (a similar problem occurs for land converted from cropland/grassland to forests). *Land Converted to Wetland* also does not appear to consider carbon stocks on the original land use type, though land conversion to wetland occurs across all land use types, including forests.

RECOMMENDATIONS

1. **Account for inland wetlands:**

   The largest gap in the wetlands section is lack of accounting for 40 million hectares of inland wetlands, as well as wetlands in Alaska, Hawaii, and U.S. Territories. Understanding the difficulty in designating managed vs. unmanaged wetlands, the United States should at least develop Tier 1 methods for accounting for all U.S. wetlands.

2. **Account for all carbon pools on Land Converted to Wetland:**

   The NGHGI should ensure calculations of *Land Converted to Wetland* GHG fluxes considers carbon stocks on the initial land use type, particularly for *Forest Converted to Wetland*.

3. **Account consistently for soil carbon stocks across land types:**

   The NGHGI should work to consistently estimate soil carbon stocks for *Land Converted to Wetland* and vice versa — e.g., ensuring equivalent depth of measurement and other calculation methods.

Table 7. Contributors to wetland uncertainty

Category	Uncertainty element	Contribution to uncertainty (MMT CO_2e)
Wetland	Soil C stock change	3.47
	Soil CH_4	0.98
	N_2O from aquaculture	0.02
	Aboveground biomass C stock change	–
Peatland	Offsite and Onsite CO_2	0.2
	Onsite CH_4	–
	Onsite N_2O	–

Alaska, Hawaii, and U.S. Territories

Alaska, Hawaii, and U.S. Territories comprise nearly 20 percent of the total U.S. land base, with nearly all of this in Alaska, yet they are not completely accounted for in the NGHGI. The 2019 NGHGI accounts for forest carbon stock changes in interior Alaska for the first time, an area covering 24.5 million acres (9 percent of U.S. managed forest area). Forest carbon is not accounted for at all in Hawaii. No LULUCF fluxes are yet calculated for the U.S. Territories, including Puerto Rico, U.S. Virgin Islands, Guam, Northern Marianas Islands, and American Samoa.

GHG FLUXES

Remaining omitted fluxes in Alaska include soil carbon stock changes in croplands and grasslands, CO_2 and methane fluxes in Alaska's vast wetlands, non-CO_2 from grassland fires, and CO_2 and N_2O from settlement soils.

Hawaii has fewer omitted fluxes, largely because it is covered by the NRI dataset, which is a key source of inputs for cropland, grassland, and settlement GHG estimates. In addition to forest carbon stock change, the NGHGI does not account for non-CO_2 from forest fires and CO_2 and methane from wetlands.

In this section we provide rough estimates of omitted GHG fluxes in Alaska, Hawaii, and Puerto Rico (which is 85 percent of the land area of U.S. Territories) to provide a sense of scale and an indicator for prioritizing calculation of GHG fluxes outside the contiguous United States.

METHODS

We use literature and emission factors derived from the NGHGI to calculate omitted fluxes. For complete information on these calculations and assumptions, see the Technical Appendix. As with all the omitted flux calculations in this report, these results are at best useful for ranking priority across fluxes rather than providing reliable estimates of flux magnitude.

We do not provide additional uncertainty analysis for Alaska, Hawaii, and U.S. Territories because our uncertainty analysis covers GHG emissions estimates in Alaska and Hawaii when they are accounted for in the NGHGI. There is additional uncertainty in Alaskan forest carbon fluxes due to different methods used to calculate forest carbon stock change in interior Alaska, along with sparser plot-level FIA data. We do not assess the uncertainty contribution from interior Alaska forest carbon methods, except to note the uncertainty is very likely higher than that for the contiguous United States and coastal Alaska.

Furthermore, there are over 46 million hectares of unmanaged U.S. land, primarily in Alaska, that are not accounted for in the NGHGI. Unmanaged lands are defined as existing over 10 km away from any road, railway system, or settlement, and not subject to any fire management. 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.

RESULTS

Table 8 lists omitted flux estimates in Alaska, Hawaii, and Puerto Rico. For additional information on how the omitted flux estimates are calculated and breakdown across omitted fluxes, see the Technical Appendix.

The largest sources of omitted fluxes are grassland soil carbon changes in Alaska, as well as soil carbon and methane emissions from Alaskan wetlands. Hawaii's forest carbon stock change is the vast majority of omitted fluxes in the state. Similarly, forest carbon stock change is the largest omission in Puerto Rico.

RECOMMENDATIONS

1. **Consider tracking fluxes on unmanaged lands:**

   The United States could provide leadership in tracking GHG emissions on unmanaged lands to improve understanding of climate impacts on land carbon. Even if these fluxes are not included in accounting for national GHG emissions reduction targets, they can still be valuable information for decision-making.

2. **Move towards tracking interior Alaska consistently with the rest of the country:**

   Interior Alaska constitutes 9 percent of U.S. forests. While we did not assess the additional uncertainty from using the interior Alaska forest carbon methods, a lower plot sampling rate is used in Alaska. As we see in the conterminous United States, sampling error is by far the largest source of uncertainty, so the challenge is larger in interior Alaska. Given the rapid changes predicted for Alaskan landscapes, greater sampling and more precise methods in interior Alaska are important.

3. **Account for Alaskan wetlands and grasslands:**

   According to a 2016 USGS analysis, these two categories represent substantial omitted fluxes, of a similar scale to Alaskan managed forest fluxes. These categories are also subject to significant changes due to climate change, making them critical for tracking and awareness.

4. **Calculate additional omitted fluxes in accordance with priority, scale, and cost considerations:**

   Additional omitted fluxes in Alaska, Hawaii, and the U.S. Territories likely represent relatively small contributions, and should be completed only as additional budgets and priorities allow. Forest carbon fluxes in each region appear to be the largest omitted categories and should be prioritized.

Table 8. Alaska, Hawaii, and Puerto Rico omitted fluxes

Negative values indicate CO_2e sequestered.

Region	GHG flux (MMT CO_2e)
Alaska	90.40
Hawaii	7.44
Puerto Rico	-0.83
Total	97.01

A Blue Sky Vision: Imagining the Ideal Greenhouse Gas Accounting System for the Land Sector

NGHGI authors have the daunting challenge of estimating GHG fluxes across all U.S. lands using existing data. Virtually no existing national datasets were designed specifically to support LULUCF GHG accounting, though some have been modified to support this effort, and no one dataset spans all land uses and land covers, nor all necessary timeframes. This requires NGHGI authors and supporting researchers to use a constellation of different datasets and methods. This results in inconsistencies across GHG accounting methods, different sources of uncertainty and methods for estimating uncertainty, and difficulty in calculating GHG fluxes from changes in land use and land cover. It also resulted in changes in the time series of LULUCF GHG estimates over time *(see Figure 5)* due to changing methods as new data becomes available, gaps in previous methods are identified, and as further efforts are made to harmonize methods across land types. Such drastic changes in LULUCF estimates each year can make policy planning difficult and undermine confidence in U.S. LULUCF GHG reporting.

For each major land type (forests, cropland/grassland, settlements, wetlands), this report has provided recommendations to address sources of uncertainty from existing methods and datasets. All of these efforts would be more incremental, "second-best" solutions, however, compared to a more dedicated, comprehensive, and publicly-accessible system for estimating land GHG fluxes across all U.S. landscapes. The benefits of a dedicated system would include:

- avoiding the need to improve and harmonize methods over time, heading off drastic changes in estimates year to year;
- avoiding gaps and biases in GHG accounting, ensuring consistent GHG estimates across the entire country;
- continually decreasing uncertainty over time by adding sample data points, with statistically valid sample design;
- consistently estimating all carbon pools for all land use types to ensure GHG flux estimates from land use and land cover change are accurate;
- reducing the effort needed to calculate the LULUCF NGHGI by using consistent methods and datasets across all land types and, if digital datasets can be used, by automating much of the process;
- and consistently scaling down national GHG flux estimates to assist policy planning and tracking at the state and local levels, which reduces duplication of GHG inventory effort and ensures consistent GHG accounting across state and local jurisdictions.

NATIONAL SYSTEM CHARACTERISTICS

Many experts have thought about the design of such a dedicated, national GHG system for the land sector. The Forest Service spent 10 years, starting in 1990, with two regional pilot studies and two blue ribbon panels, developing the national Forest Inventory and Analysis (FIA) plot and data system that exists today, which is a useful template for what the national system could look like (Bechtold and Patterson 2005). Spencer et al. (2011) proposed a similar system for national soil carbon monitoring. Based on these examples, we propose a national LULUCF GHG accounting system with the characteristics outlined below.

Objectives

The nationally-consistent LULUCF GHG accounting system would estimate national and sub-national changes in carbon stock (which results in CO_2 sequestration and emissions) and other sources of CO_2 and non-CO_2 emissions from land use, land management, and agriculture. "Consistency" is a key objective because it means any estimation bias or gaps in GHG accounting are minimized *(see Section 2 for more discussion on bias and uncertainty)*. Data within this system would be regularly updated on time scales meaningful for policy planning and tracking, using best available methods for data collection, including satellite data. Methods used in this system would allow for attributing drivers of carbon stock change and GHG emissions to further support policy development and tracking.

Sample plot system

Nearly every component of the LULUCF NGHGI depends in some way on plot-level estimates of carbon stock, which are then extrapolated to larger areas to estimate national GHG fluxes. However, each land use type depends on a different dataset for sample plots, and not all samples are derived through random sampling. Different land types benefit from different numbers of sample plots.
For example, the FIA plot system used for forest carbon measurements is randomly sampled across the entire country (except some parts of Alaska and Hawaii), while

the data currently used for urban tree plots in the NGHGI is based on previous studies and locally funded measurements, along with some FIA urban plot measurements. Cropland and grassland have a nationally randomized plot system through the National Resources Inventory (NRI), but generally carbon measurements are not taken at plot sites.[12]

In a dedicated system, a nationally randomized plot system would cover all land use and land cover types, with direct carbon measurements across all five carbon pools (aboveground biomass, belowground biomass, dead wood, litter, and soil) at every plot. Best available science would govern consistent carbon measurements across all land types, prioritizing, for example, one meter depth of soil carbon measurement wherever possible (Stockmann et al. 2013). Where relevant, management practices would also be collected at each plot. For example, cropland plots would record tillage practices, fertilizer application, and other variables critical for extrapolating plots to national estimates. The USDA Natural Resource Conservation Service's Conservation Effects Assessment Project (CEAP) collects similar data at a subset of NRI points to estimate the effects of conservation practices, and a similar system could be scaled up across more plot points and carried out regularly over time. Management data would be especially useful for wetland areas, for which data does not currently exist for determining which wetlands are managed versus unmanaged.[13] Consistently measuring carbon pools across all land areas would also address gaps in the current NGHGI, like not measuring biomass carbon stocks on cropland and grassland.

Additional management data could be collected through randomized surveys to farmers and ranchers, if there is a concern that plot-based data is not adequately capturing the diversity of management practices.

Use of remote sensing data to augment plot data

Plot data is valuable but expensive to gather. More data than ever before is available to track landscape dynamics from satellite imagery and other remote sensing data like LiDAR. To augment plot data, the national LULUCF GHG system should develop methods to track carbon stock changes at plot level, or even at landscape scale, using remote sensing data. This data could also be used to more finely stratify U.S. landscapes, meaning individual plots would correspond to smaller land areas that are more closely correlated to the plot attributes, which is another important opportunity to reduce sampling error in the GHG inventory.

New NASA missions like GEDI and ICESat-2 are collecting LiDAR and other data to estimate the height of the Earth's surface, which combined with more traditional LandSat or MODIS imagery and information on slope and climate, can allow for estimating aboveground biomass. Research is ongoing to increase the accuracy of aboveground biomass predictions (Blackard et al. 2008; Lu et al. 2016; McRoberts et al. 2016; Ma et al. 2018). The national land sector GHG system should participate in and support this research, and ensure that satellite data is used to reduce overall costs and allow for regular updates to the inventory over time. A 21st century GHG monitoring system would be incomplete without taking full advantage of remote sensing technology.

National land representation dataset

The current NGHGI uses at least four different datasets to determine changes in area of forest, cropland, grassland, settlement, and wetlands: FIA, NRI, NLCD, and NOAA C-CAP. Inconsistency across how datasets define land use and land cover types results in uncertainty and additional work to harmonize land area estimates across NGHGI sections.

The dedicated GHG system would have a single national land representation dataset that consistently stratifies the entire U.S. land base across land use and land cover types, and could incorporate additional stratification variables like forest canopy cover, forest type, soil type, crop type, wetland type, etc. The dataset could be updated annually using satellite data. The dataset would also be designed to easily downscale to the state and local levels.

Ongoing research

Throughout this report, we note the uncertainty contributed through model structure and parameters. Ongoing research and measurements beyond sample plot data will be needed to improve parameter estimates and model development.

For example, this report identifies that some of the largest sources of uncertainty in forest carbon estimation are parameters that convert tree diameter into tree volume and total tree biomass. A dedicated GHG system would fund new studies that better randomly sample across tree species, tree ages, tree sizes, climates, and other variables to estimate these parameters.

The research arm of the dedicated GHG system would provide consistent parameters and model development across carbon pools and land types. This report can help identify top priorities for model and parameter research, focusing on the elements that contribute the largest amount of uncertainty in the current NGHGI.

12. Soil carbon measurements were taken at a subset of NRI plots as part of the Rapid Carbon Assessment initiated in 2010 (USDA 2013).
13. Unmanaged landscapes are not included in the NGHGI, because GHG fluxes in those regions are not directly driven by human activity.

Research can also support basic scientific understanding of issues like soil carbon and nutrient cycling and optimal strategies for modeling soil carbon dynamics, which, as we note below, contribute uncertainty to cropland and grassland GHG fluxes.

Consistent modeling methods

Due to the diversity of available data and because different research teams work on the various components of the LULUCF NGHGI, different models and methods are used for each land type. This is a challenge with soil carbon estimates, which is the one carbon pool that is estimated over nearly all managed U.S. land area, but with different models used for each land category. If all carbon pools are estimated for all land types this issue will increase in importance.

The dedicated GHG system would ensure all carbon pools are modeled consistently across land types. New models may be needed to flexibly estimate carbon from, for example, forest trees as well as orchard trees and urban trees. Development of these broader models would allow for consistently estimating carbon and uncertainty across land types.

The research arm of the dedicated GHG system would allow for regularly updating models with consistent, data-based parameter values and comparing model outputs with plot carbon measurements.

Public accessibility

The underlying data in the current NGHGI has varying levels of transparency for the public. Most of the data is publicly available, except NRI. Compiling the data for independent analysis like this project can be quite cumbersome, however, especially as much of the data is disaggregated in individual studies.

A dedicated GHG system would prioritize transparency for the public and the research community, clearly publishing datasets, underlying parameters, sources of uncertainty, and estimation methods for all. In order to make some of the data fully public, "fuzzing and swapping" of plot-level data is required, so that plot locations and data on private lands are protected. FIA already undertakes fuzzing and swapping, which means the data for each plot is swapped with another similar plot and plot locations are shifted by up to a mile away from the true location. This limited inaccuracy is acceptable in exchange for greater transparency, but it creates challenges for spatially-explicit modeling and requires working directly with whichever agency owns the data if spatial accuracy is required.

Outreach and education is a key component of public accessibility. FIA occasionally provides trainings for how to use the dataset, which is quite complex. The future dedicated GHG system would make such trainings a priority, with a regular schedule covering data for all land types.

CHALLENGES

There are several challenges to developing a comprehensive national LULUCF GHG system.

First, the Intergovernmental Panel on Climate Change (IPCC) requires that nations use consistent methods across time to estimate GHG emissions. That is, "the time series should be calculated using the same method and data sources in all years" (IPCC 2006). New datasets and methods, even if they improve upon earlier methods, may be difficult to back-cast to 1990 (the earliest inventory year of the current NGHGI) and even further to 1971 (IPCC guidance requires knowledge of land use 20 years prior to the first inventory year). Ultimately, the United States government will need to navigate the pros and cons of inconsistent reporting across time against significantly improving inventory methods going forward, and follow IPCC guidance to integrate different methods across the time series. There is also the option of using improved inventory methods to inform domestic national policy while consistent time series methods are used for IPCC reporting, although this would be suboptimal due to duplication of effort.

More importantly, GHG inventory efforts are expensive. As of 2016, the FIA annual budget is $75 million (Reams 2017). FIA is only one part of the LULUCF NGHGI, but its efforts are not solely focused on the NGHGI. Ideally, the dedicated land sector GHG system could draw from existing funding pots, like FIA and NRI. The new system could, in theory, simply provide an overarching framework for these existing data platforms to coordinate and expand to other land types like settlements and wetlands, with the objective of a completely consistent national dataset. Sources and scale of funding would be a critical aspect of feasibility analysis if the new dedicated GHG system were to be developed.

Lastly, a perennial challenge for the federal government is coordination across agencies. While it may seem trivial, different agencies have different mandates, spending authorities, and political constituencies. This makes it difficult for agencies in charge of different datasets to harmonize data collection methods or even coordinate modeling efforts. Political will and central leadership will be required to implement a dedicated national GHG accounting system, building on decades of expertise and existing funding sources across U.S. federal agencies.

RECOMMENDATIONS

Similar to the process of developing the annual FIA data and plot system, expert input and planning will be required to establish a consistent national GHG inventory system for the land sector. We propose as a next step to this report that a blue ribbon panel be convened to assess how the success of the FIA system can be applied to the entire country, to identify how much of this system could be comprised of existing programs and funding, and to identify what additional work and funding would be required to implement this system. Such a process is likely to take many years, so expediting the work of such a panel is critical to putting in place a nationally-consistent GHG accounting system as quickly as possible.

Conclusion

In this report, we summarized the contribution of over 90 elements to uncertainty and accuracy in the land use, land use change, and forestry (LULUCF) greenhouse gas inventory, along with several key agriculture components *(see Table 1 for project scope)*.

Much of the uncertainty and omitted fluxes are driven by a few key categories, including:

- Sampling error in estimating carbon in forest biomass;
- Omitting carbon changes in Alaskan grasslands and wetlands;
- Using a “gross to net” sequestration ratio in calculating carbon changes in urban trees, which is not consistent with forest carbon accounting methods;
- The modeling parameters used to convert tree diameter into tree volume and tree biomass;
- Omitting carbon changes in urban mineral soils; and
- Modeling carbon changes in cropland and grassland mineral soils based on soil properties.

The top 10 elements account for nearly three quarters of total uncertainty, meaning that addressing a few key areas could significantly reduce the uncertainty in LULUCF GHG flux estimates. However, addressing the largest sources of uncertainty and omitted fluxes will likely require large-scale investment.

Addressing sample error from forests is likely to be one of the more costly issues to address since it could require increasing the number of FIA plots measured each year, but more cost-effective remote sensing methods could also be employed to reduce sampling error. Incorporating more Alaskan landscapes into the NGHGI would also require plot measurements and parameterized carbon models for this region.

Other sources of uncertainty that require additional data and research might be possible to address through existing budgets, like addressing the methods for calculating urban tree carbon, re-estimating parameters for forest carbon models, and better characterizing urban soils. We hope the analysis in this report can point federal experts towards priorities and sequencing for carrying out new research and data collection.

The analysis in this report used simplifying assumptions throughout, primarily by assuming independence across calculation factors and input data in most cases. Experts with access to raw data could replicate this work and investigate the effect of assuming correlation across various elements, which would lead to lower overall levels of uncertainty. Such verification and recalculation would be welcome. In most instances, we take NGHGI reported uncertainties at face value and use these to derive uncertainty contributions or our calculated uncertainty is close to that reported in the NGHGI. Furthermore, our objective here was not to estimate total NGHGI uncertainty, but rather to attribute sources of uncertainty—assuming correlation across variables is unlikely to significantly change the ranking we have identified here.

It is important to understand that it will never be possible to fully eliminate uncertainty from the NGHGI, and this is not a reasonable objective. Rather, this exercise is meant to help identify priorities for reducing uncertainty from the components of the NGHGI that comprise 70 percent of total inventory uncertainty, and for which there remain omitted GHG fluxes. While we hope the United States will move towards a comprehensive, dedicated LULUCF GHG accounting system in the future *(see Section 8: A Blue Sky Vision)*, in the meantime incremental steps can be taken to increase confidence in the NGHGI both domestically and internationally, to avoid large changes in LULUCF estimates over time, and to improve policy-making capacity.

References can be found at the end of the Technical Appendix.