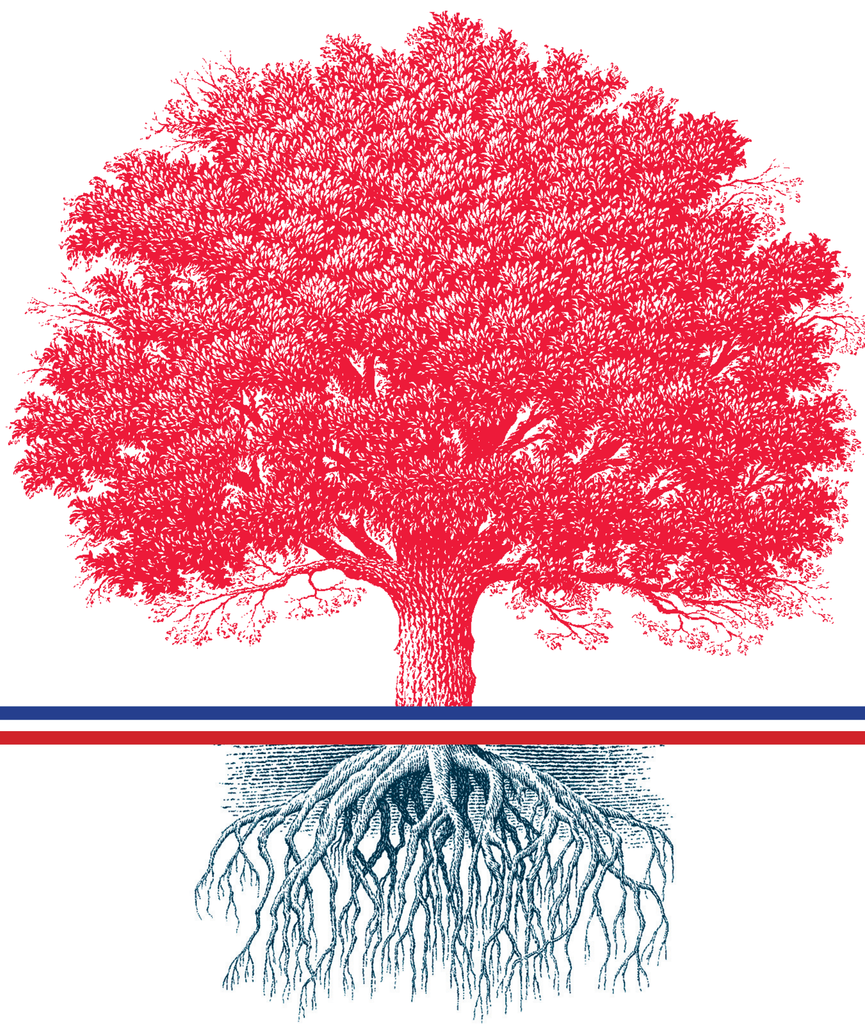
United States Department of Agriculture

The U.S. Forest Carbon Accounting Framework: Stocks and Stock Change, 1990-2016



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ABSTRACT

As a signatory to the United Nations Framework Convention on Climate Change, the United States annually prepares an inventory of carbon that has been emitted and sequestered among sectors (e.g., energy, agriculture, and forests). For many years, the United States developed an inventory of forest carbon by comparing contemporary forest inventories to inventories that were collected using different techniques and definitions from more than 20 years ago. Recognizing the need to improve the U.S. forest carbon inventory budget, the United States is adopting the Forest Carbon Accounting Framework, a new approach that removes this older inventory information from the accounting procedures and enables the delineation of forest carbon accumulation by forest growth, land use change, and natural disturbances such as fire. By using the new accounting approach with consistent inventory information, it was found that net land use change is a substantial contributor to the United States forest carbon sink, with the entire forest sink offsetting approximately 15 percent of annual U.S. carbon dioxide emissions from the burning of fossil fuels. The new framework adheres to accounting guidelines set forth by the Intergovernmental Panel on Climate Change while charting a path forward for the incorporation of emerging research, data, and the needs of stakeholders (e.g., reporting at small scales and boreal forest carbon).

Quality Assurance

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The U.S. Forest Carbon Accounting Framework:

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C.W. Woodall is the carbon accounting group leader for the Forest Inventory and Analysis (FIA) program and coordinated the development of this new accounting approach and creation of this GTR.

C.W. Woodall, J.W. Coulston, G.M. Domke, B.J. Clough, M.C. Nichols, C.H. Perry, and M.B. Russell developed the initial framework for carbon accounting at a workshop in October 2014.

J.W. Coulston and D.N. Wear developed the R code and techniques for projecting annual forest inventory, separating land use change from forests remaining forest and attribution to disturbance.

G.M. Domke developed new techniques for estimating litter and soil organic carbon.

B.F. Walters conducted the majority of the FIA database development for this project and created infographics and maps.

J.E. Smith contributed writing material.

H.-E. Andersen contributed information on Alaska's carbon accounting.

B.J. Clough contributed the Bayesian uncertainty description.

W.B. Cohen contributed the Landsat/LiDAR research description.

D.M. Griffith contributed carbon pool maps.

S.C. Hagen contributed the NASA-Carbon Monitoring System study description and results.

I.S. Hanou contributed to the description and development of the phone and tablet carbon application.

C.H. Perry contributed the U.S. forest carbon in context infographic.

M.B. Russell contributed to the pool estimation and phone application description.

J.A. Westfall contributed the national volume/biomass study description.

B.T. Wilson contributed carbon maps and the disaggregation description.

PREFACE

A Modeling System That Moves Annual Forest Inventory Data through Time and Attributes Changes to Disturbances and Land Use

The United States is currently in the process of adopting a new approach to forest carbon accounting. The Forest Carbon Accounting Framework (FCAF) will incorporate the most consistently measured annual forest inventories (including all the pools of forest carbon) while aligning with projections of forest resources. Such an approach will reduce inconsistencies, and thus uncertainty, associated with the U.S. forest carbon baseline while empowering policy makers in light of potential future greenhouse gas emission reduction targets.

One role for the new framework is meeting the reporting commitments for the United States under the United Nations Framework Convention on Climate Change (UNFCCC). The forest ecosystem carbon estimates contained herein are initial estimates from the new FCAF that is in development for official release as part of the National Greenhouse Gas Inventory submission of the United States to the UNFCCC in 2016. The United Nations Intergovernmental Panel on Climate Change documents Good Practice Guidance (IPCC 2006) for several attributes that national carbon inventories should aspire to: transparency, consistency, comparability, completeness, and accuracy. In this context transparency means that the data sources, assumptions, and methodologies are clearly documented. Consistency assures the estimates for all reported inventory years account for changes in data or methods over time. Forest carbon inventories should also be comparable across Nations, an attribute that is empowered by clear documentation. Completeness refers to the identification of all appropriate carbon in forest ecosystems (i.e., pools). Accuracy is attained by removing bias and minimizing uncertainty as much as is practically possible. The new FCAF of the United States seeks to embrace all these tenets through the development of a novel accounting approach that addresses attribution (i.e., disturbances) and land use change and incorporates emerging science and diverse data sources, all while providing clear documentation such as we have done in this first publication.

Forest Inventory and Analysis field crew measuring a plot in southeast Alaska. Photo by U.S. Forest Service.

CONTENTS

INTRODUCTION

Carbon dioxide is one of the most important greenhouse gases that contributes to the warming of our planet via the greenhouse gas effect. Carbon is emitted through the combustion of fossil fuels and through the decay and combustion of organic material such as wood. In contrast, carbon can be sequestered through the growth of trees. Recognizing the need to monitor the emission and sequestration of carbon on Earth, the United Nations Framework Convention on Climate Change (UNFCCC) called for the annual monitoring of carbon among signatory Nations. This annual monitoring mechanism is known as a National Greenhouse Gas Inventory (NGHGI) which contains accounting of carbon emissions and removals (i.e., sequestration). The United States is a signatory to the UNFCCC whereby annual inventory reports of carbon are developed. This document provides additional information on the context of the U.S. forest carbon cycle, a brief history of carbon accounting efforts, and a vision for the future of forest carbon accounting in the United States.

Of all the land uses across the United States (e.g., settlements, croplands, or wetlands), forests sequester the vast majority of carbon from the atmosphere, which partially offsets carbon emissions from sources such as fossil fuel combustion. Due to this important role of forests in the carbon budget, there is a continuous effort to improve the accounting of forest carbon across the diverse ecosystems and ownerships of the United States. In this document we introduce a new approach to forest carbon accounting in the United States, the Forest Carbon Accounting Framework (FCAF). Across this broader document you will gain access to preliminary estimates from the 2016 carbon inventory of U.S. forests using the FCAF along with contextual analysis of these estimates. In addition, because new data and scientific advances occur annually, planned inventory improvements and promising research directions will be outlined as a potential roadmap for the future.

The U.S. Forest Carbon Cycle in Context

Currently, annual net sequestration of carbon in managed U.S. forests offsets approximately 15 percent of the annual emissions of carbon that result from the combustion of fossil fuels (Fig. 1). In addition, forests contain substantial stores of carbon which have accumulated in some pools (e.g., soils) for millennia. The amount of carbon stored in U.S. forests represents more than 67 years of fossil fuel emissions at today’s rate of combustion (see Forest Carbon Vital Signs on page 7). However, just as there are numerous sources of fossil fuel emissions, including electrical generation and transportation, the forest also has numerous carbon pools that emit carbon through decay and combustion. An important difference is that forest carbon pools also serve as active sinks of carbon, in strong contrast to fossil fuels which can only serve as an emission source. New biomass that arises from forest growth and expansion that is not emitted via decay or combustion can serve as a longer-term store of carbon as a wood product, by being assimilated into the forest floor or soils, or by remaining in their constituent pool (i.e., old growth forests). Without the continued expansion and growth of forests, their ability to serve as a substantial offset of U.S. fossil fuel emissions will be diminished.

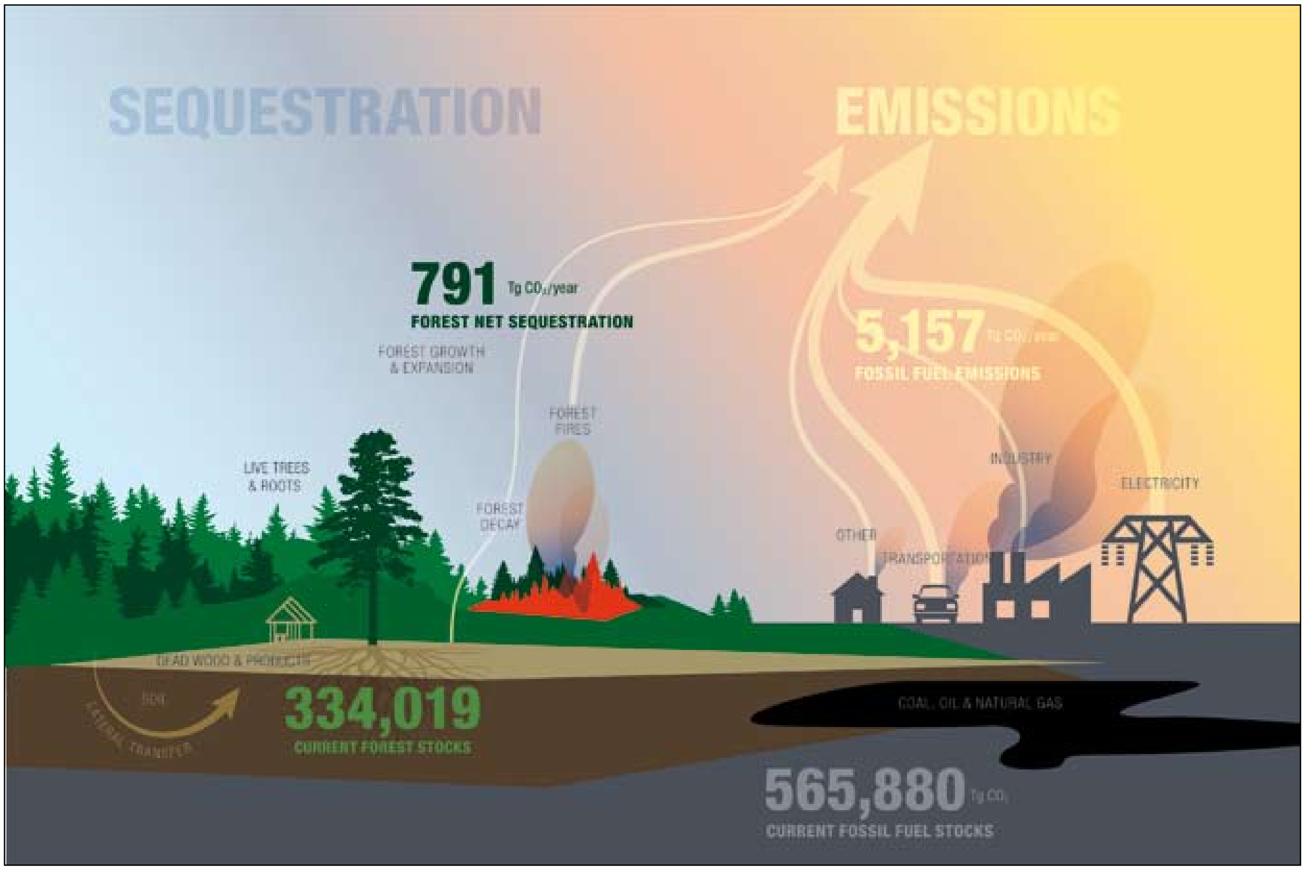


Figure 1.—The components of the U.S. forest carbon cycle (2016 estimates, pools, and flow) in the context of fossil fuel emissions (values for fuel emission estimates from USEPA 2015a). Diagram courtesy of Perry et al. (in press).

Forest Carbon Inventories: A History of Improvements

In the United States, monitoring forest carbon has been a process of continuous improvement as data (both field and remotely sensed) have accumulated in the face of emerging research (e.g., carbon pool science) (Fig. 2). In the 1990s, Birdsey (1992) converted a compendium of periodic forest inventories into carbon assessments using numerous assumptions about volume to carbon conversions. In the 2000s, Heath and Smith ushered in a new era of carbon reporting (Smith et al. 2010) that focused on comparing the nationally consistent annual forest inventories to past periodic inventories to estimate carbon change. In the 2010s, carbon monitoring (Woodall 2012) has focused on improving pool estimation using the full breadth of the national forest inventory system (e.g., including soil measurements) while developing approaches to incorporate emerging remotely sensed information (e.g., Landsat and LiDAR) and aligning with projection systems.

The Forest Carbon Accounting Framework Vision

In response to calls for improved terrestrial carbon accounting in the United States stemming from the Agricultural Act of 2014, also known as the 2014 Farm Bill (Agricultural Act 2014), and the President's 2013 Climate Action Plan (U.S. Executive Office of President 2013), a cohesive carbon accounting framework (the FCAF) was envisioned that linked the Forest Inventory and Analysis (FIA) annual inventory system of all forest carbon pools to modules that compile predictions of carbon stocks and stock changes back to the 1990

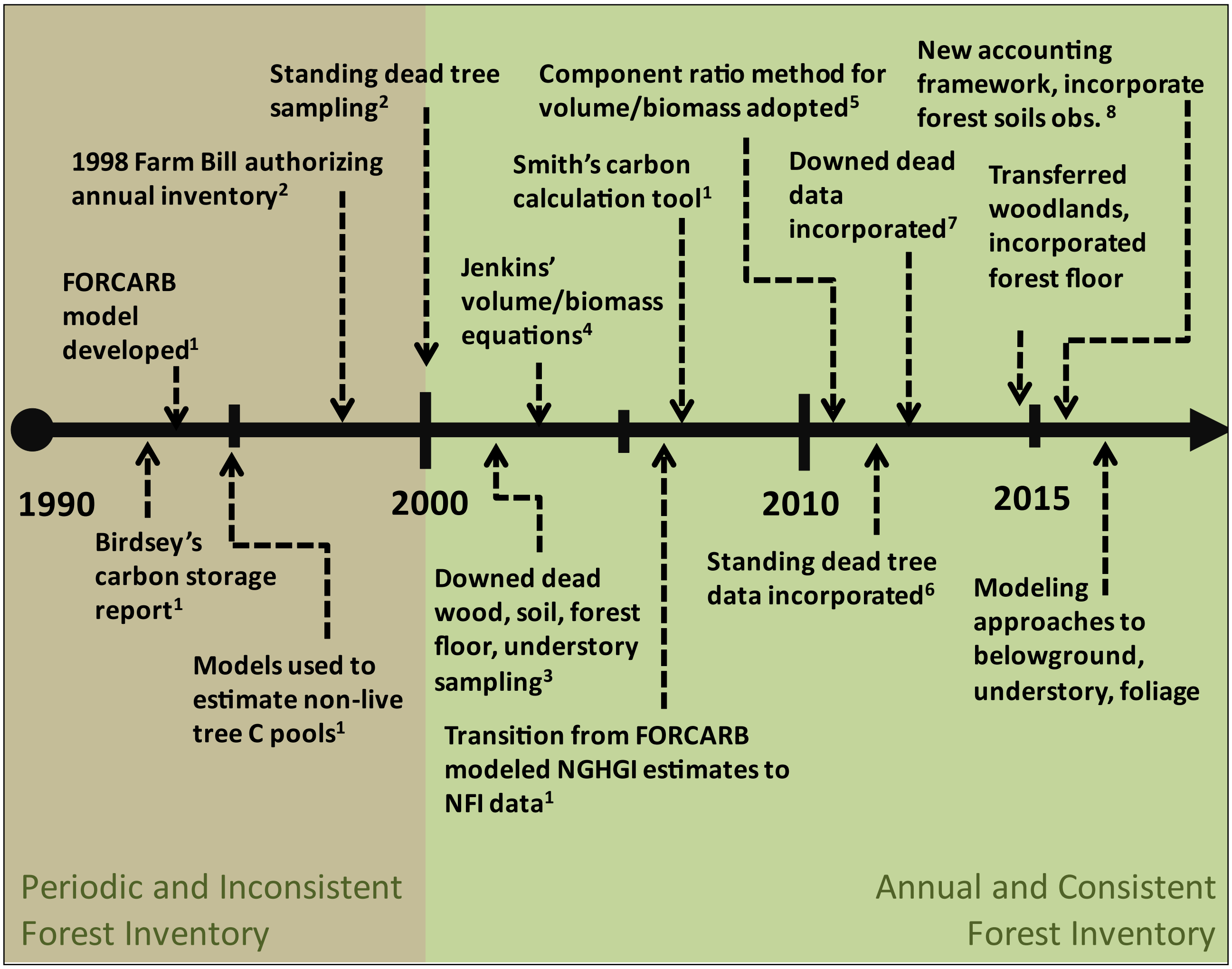


Figure 2.—Timeline of the development of national greenhouse gas inventories for U.S. forests showing the phasing out and replacement of periodic forest inventories with annual forest inventories. References include: [1](Birdsey 1992, Birdsey and Heath 1995, Birdsey 1996, Heath et al. 1996, Smith et al. 2010); [2](U.S. Forest Service 2014a, U.S. Forest Service 2015a); [3](Woodall et al. 2011a); [4](Jenkins et al. 2003); [5](Woodall et al. 2011b); [6](Woodall et al. 2012); [7](Domke et al. 2013); [8](See this publication; Domke et al., in prep.). NGHGI = National Greenhouse Gas Inventory; NFI = National Forest Inventory.

baseline and forward to user-defined time horizons. Recognizing the host of obligatory forest carbon reporting needs (e.g., United Nations Framework Convention on Climate Change [UNFCCC 2015a], Global Forest Resources Assessments [UN FAO FRA 2015], United Nations Framework Convention on Climate Change Biennial Reports [UNFCCC 2015b], Montréal Process Criteria and Indicators [Montréal Process Working Group, n.d.], and U.S. Forest Service Climate Change Scorecard [U.S. Forest Service 2015b]), the new framework had to be able to estimate the carbon implications of disturbances and management and disaggregate land use change into deforestation versus afforestation effects on carbon stocks and stock changes at national and regional scales (Fig. 3). Past approaches (Fig. 3a) often depended on reconciling differences between two different U.S. forest inventory systems, which had a higher probability of creating carbon flux estimates stemming from differences in sample design rather than changes in forest ecosystems. Furthermore, this previous accounting approach did not easily enable linkage to forecasting mechanisms (Fig. 3a). The new, data-driven accounting framework (Fig. 3b) has already been designed for implementation at the strategic scale using the national forest inventory of the United States, and with the appropriate data the framework can be used by partners interested in carbon accounting at other spatial scales of interest. Beyond the peer review and publication of all technical aspects of this vision, an outreach and extension component still needs to be developed to interpret the results of the new accounting system for policy makers, land managers, and citizens.

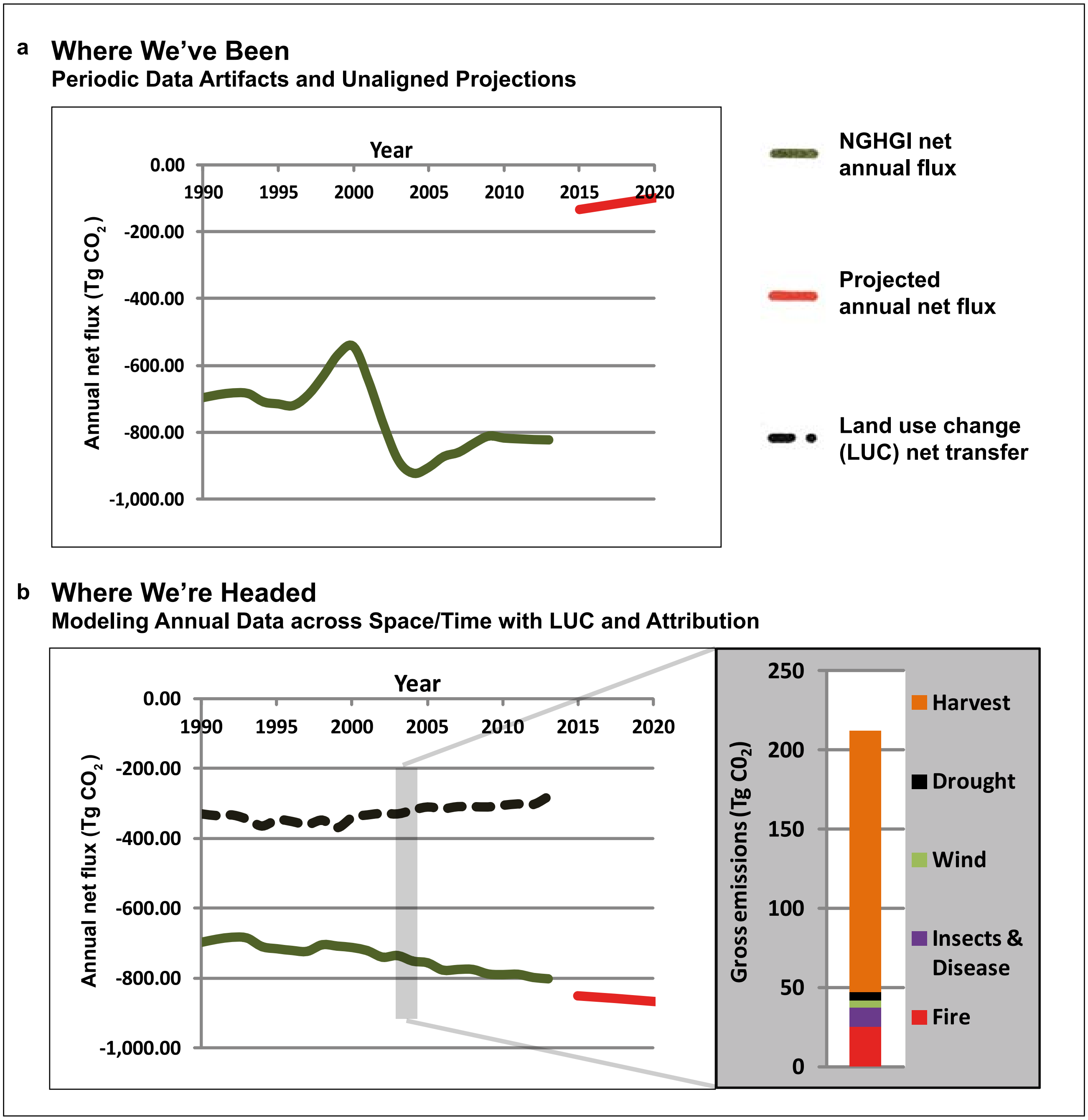


Figure 3.—Hypothetical carbon baselines that illustrate past issues with forest carbon accounting techniques, namely (a) misalignment between current baselines and future projections in addition to a lack of attribution to disturbance. It is expected that (b) future forest carbon baselines using the techniques described in this document will align baselines with projections while affording attribution to disturbance.

How do the Forest Carbon Estimates in this Report Differ from Previous Greenhouse Gas Inventories?

- Older, periodic inventories which did not cover all managed forest land and were inconsistent with current annual inventories were removed from the accounting system, thus removing inconsistencies and reducing carbon baseline uncertainty.
- A new modeling approach was used to generate estimates of forest carbon derived from the annual inventory system both backward (to 1990) and forward (to 2016) through time to satisfy UNFCCC requirements.
- Repeated measures of the hundreds of thousands of permanent plot locations were used to inform land use change and disturbance effects on carbon stocks.
- In the eastern United States, remeasured individual plots were used to estimate carbon stocks and change. For the western states, the FIA annual inventory panel design was divided into two distinct time periods, with the older and more recent periods representing two independent estimates of the forest carbon population. In the future, as annual plots are remeasured in the western states, this approach can be replaced with remeasured annual plots, per the technique adopted for eastern states.
- Harvested wood products were not included in this forest ecosystem carbon assessment but will be included in the upcoming UNFCCC submission.
- This analysis focuses solely on the forest sector, so carbon transfers to other land uses were subtracted from the forest carbon inventory but were not reconciled with estimates made independently for other land sectors as will be required for the United States submission under the UNFCCC.
- A new approach for estimating soil organic carbon, the largest pool of carbon in U.S. forests, was included in this analysis (Domke et al., in prep.). The approach builds on the thousands of in situ observations from across U.S. forests in conjunction with modeling refinements developed in coordination with the International Soil Carbon Network (ISCN; http://iscn.fluxdata.org/Pages/default.aspx).

What is a Forest?

The UNFCCC does not prescribe to a specific definition for forest, but instead each country determines its own classification. Starting with the 2015 National Greenhouse Gas Inventory report (USEPA 2015a, b) and for this report, forest land is defined as: Land at least 120 feet (37 m) wide and at least 1 acre (0.5 ha) in size with at least 10 percent cover (or equivalent stocking) by live trees, including land that formerly had such tree cover and that will be naturally or artificially regenerated. Trees are woody plants having a more or less erect perennial stem(s) capable of achieving at least 3 inches (7.6 cm) in diameter at breast height, or 5 inches (12.7 cm) diameter at root collar, and a height of 16.4 feet (5 m) at maturity in situ. The definition here includes all areas recently having such conditions and currently regenerating or capable of attaining such condition in the near future. Forest land also includes transition zones, such as areas between forest and nonforest lands, that have at least 10 percent cover (or equivalent stocking) with live trees and forest areas adjacent to urban and built-up lands. Unimproved roads, trails, streams, and clearings in forest areas are classified as forest if they are less than 120 feet (37 m) wide or an acre in size. Forest land does not include land that is predominantly under agricultural or urban land use (Oswalt et al. 2014: 31).

Forest and hayfield in southern Indiana. Photo by Christopher Woodall, U.S. Forest Service.

How Much Forest in the United States is Managed?

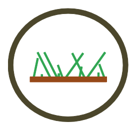
Approximately 34 percent (310 million ha) of the U.S. land area is estimated to be forested (Oswalt et al. 2014). The most recent forest carbon inventories from each of the conterminous 48 states (U.S. Forest Service 2014a, b) includes an estimated 264 million ha (Oswalt et al. 2014) of forest land that are considered managed (Ogle et al., in prep.) and are included in this inventory. An additional 6 million ha of southeast and south central Alaskan forest are inventoried and are included in this analysis. Annual forest inventory data are not yet available for Hawaii and interior Alaska, but estimates for these areas are included in Oswalt et al. (2014).

Standing dead tree in Superior National Forest in Minnesota. Photo by Christopher Woodall, U.S. Forest Service.

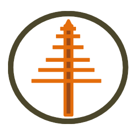
What is in a Forest Carbon Pool?

Carbon estimates obtained directly from an inventory or from inventory-based models are classified to account for all forest ecosystem organic carbon and fall into the following distinct, non-overlapping, forest ecosystem carbon pools which can be arrayed in various combinations for domestic or international (e.g., UNFCCC) reporting:

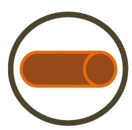
Live tree biomass—biomass of all live trees with a diameter of 2.5 cm and greater measured 1.37 m above the forest floor (diameter at breast height; d.b.h.) including stem, stump, branches, bark, and belowground coarse living roots with a diameter greater than 2 mm.



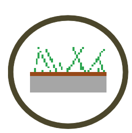
Understory vegetation—all live biomass including woody shrubs and trees smaller than the above tree classification, specifically less than 2.5-cm d.b.h.



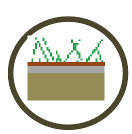
Standing dead trees—entire aboveground and belowground portions of standing dead trees with a d.b.h. of 12.7 cm and greater.



Downed dead wood—all nonliving woody material lying on the ground and having a diameter greater than 7.5 cm at transect intersection. This pool also includes stumps (both aboveground and belowground portions).



Forest floor or litter—includes the duff, humus, and fine woody debris located above the mineral soil, and all nonliving woody biomass with a diameter less than 7.5 cm at transect intersection, lying on the ground.



Soil organic carbon (SOC)—all organic material in soil to a depth of 1 m, including fine roots but excluding the coarse roots of the belowground pools.

FOREST CARBON INDICATORS

Forest Carbon Vital Signs

A number of key statistics regarding U.S. forest carbon using the new FCAF are presented in Figure 4. It is useful to policy makers to evaluate forest carbon rates relative to other sectors such as fossil fuel emissions. Please refer to the Carbon Stocks and Stock Change section on page 12 for complete national results.

67 Years

Time needed for cumulative U.S. fossil fuel emissions of carbon (at current rates) to equal the total amount of carbon stored in U.S. forests

From 1990 to the Present	
Average Annual Net Forest Sequestration	204.9 Tg C yr^{-1}
Net Change in Land Use Change as Percentage of Forest Sink	+3%
Gross Increase in Total Ecosystem Carbon Stocks	5,338 Tg C
Net Change in Managed Forest Land Area	+10,835,218 ha
Forest Carbon Pool with Largest Percentage Increase in Stocks	Live Trees

15 %

Amount of annual emission of carbon from combustion of fossil fuels in the U.S. currently offset by growth and expansion of U.S. forests

From 2005 to the Present	
Average Annual Net Forest Sequestration	214.7 C Tg C yr^{-1}
Net Change in Land Use Change as Percentage of Forest Sink	-1.3%
Gross Increase in Total Ecosystem Carbon Stocks	2,377 Tg C
Net Change in Managed Forest Land Area	+4,576,753 ha
Forest Carbon Pool with Largest Percentage Increase in Stocks	Live Trees

Figure 4.—Key statistics for annual U.S. forest carbon monitoring derived from the new Forest Carbon Accounting Framework introduced in this document.

The U.S. Forest Carbon Baseline

Overall, the total net carbon stock change (i.e., net sequestration) provided by U.S. forests has been trending above 200 Tg C yr^{-1} since the Great Recession began in 2007 (Fig. 5a). There has been more fluctuation in net forest sequestration (i.e., net growth) due to the effects of variations in regional harvest patterns which have a stronger effect on sequestration than wildfire (Fig. 5b). Land use change has been a steady net positive contributor to the forest carbon sink, with a slight decrease in the positive rate of change in recent years (Fig. 5a).

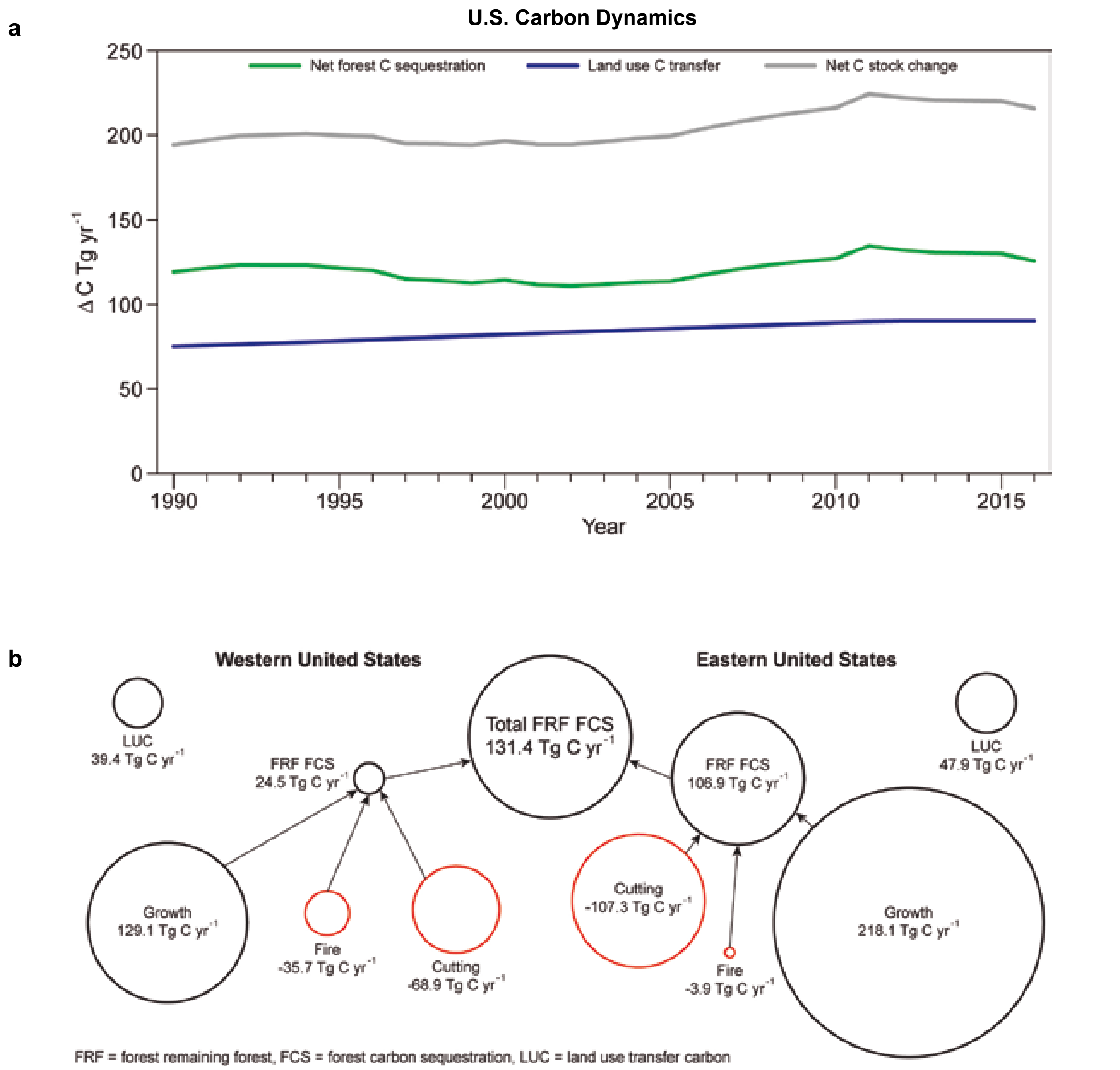


Figure 5.—The 1990-2016 forest carbon baseline (a) and 2011 attribution to disturbance (b), including delineation between forests remaining forest and land use change, obtained from the new Forest Carbon Accounting Framework in managed forests of the United States.

The Carbon Baseline in Context

Although trends in land use and net forest growth in relation to the forest carbon baseline have only marginally varied over the past couple of decades, more conclusions can be drawn when viewing these trends relative to the total forest sector and fossil fuel emissions (Fig. 6). As carbon from U.S. fossil fuel emissions has slightly diminished over the past few years, the offset from both land use change and net forest growth have increased, from lows of 5.3 and 7.2 percent in the early 2000s, to recent highs of 6.4 and 9.3 percent, respectively. Relative to the entire forest ecosystem sector, net forest growth since the Great Recession has represented a larger proportion of the forest ecosystem sink than carbon transfers resulting from net land use change to forests.

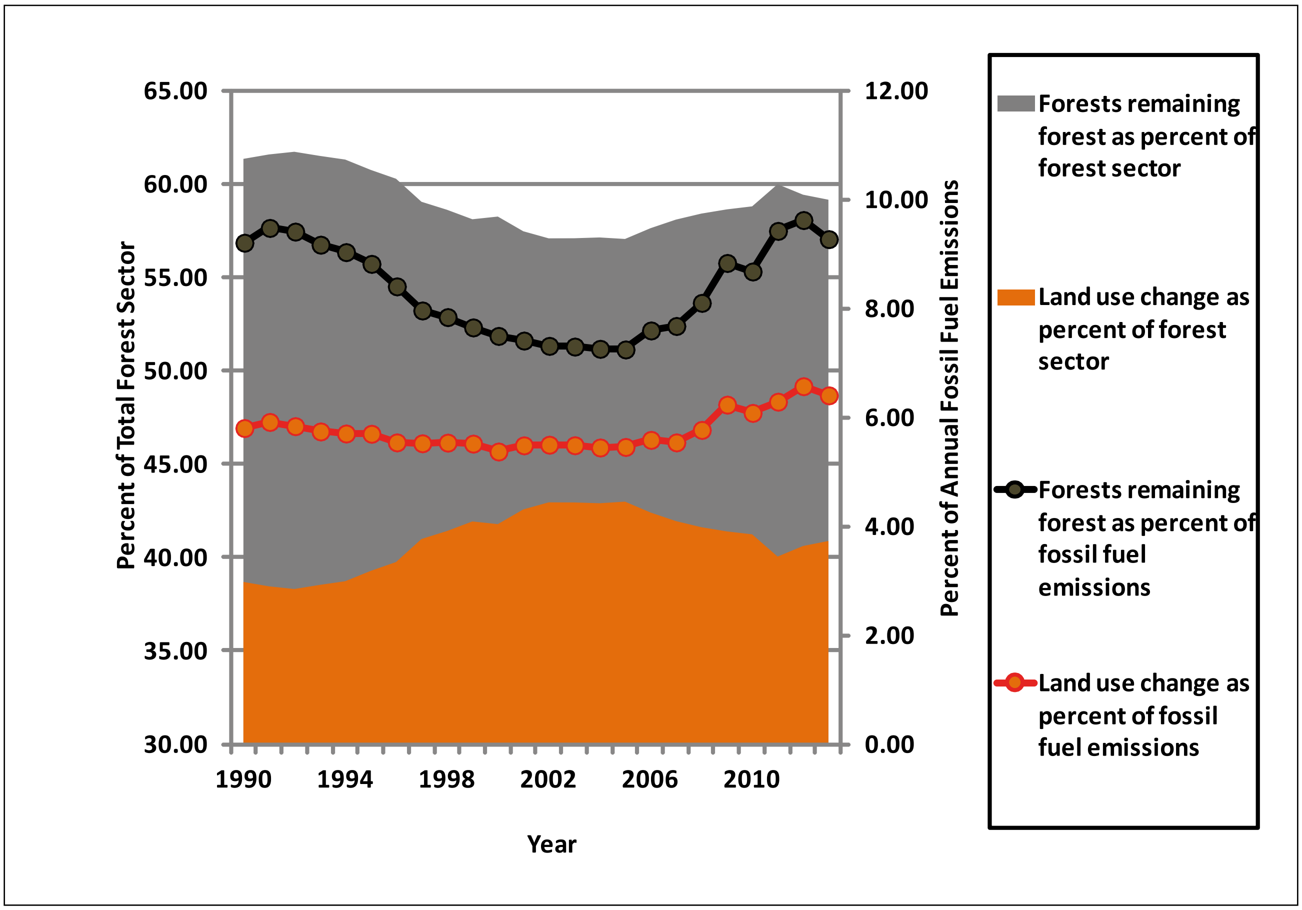


Figure 6.—Net annual sequestration resulting from forests remaining forest (i.e., net forest growth) versus land use change (i.e., net carbon transferred into forests from other land uses) relative to the forest ecosystem carbon sink and carbon from fossil fuel emissions.

Forest Carbon Stocks and Pools

Carbon pools are the individual, nonoverlapping categories where carbon resides in a forest, such as soils or live trees. Stocks are the amount of carbon in each particular pool. Figure 7 displays the proportion of U.S. carbon stocks by pool and as a coal equivalent, and also shows the spatial delineation of each carbon pool across the United States. In some regions, such as the upper Great Lakes, the majority of forest carbon resides in the soils pool.

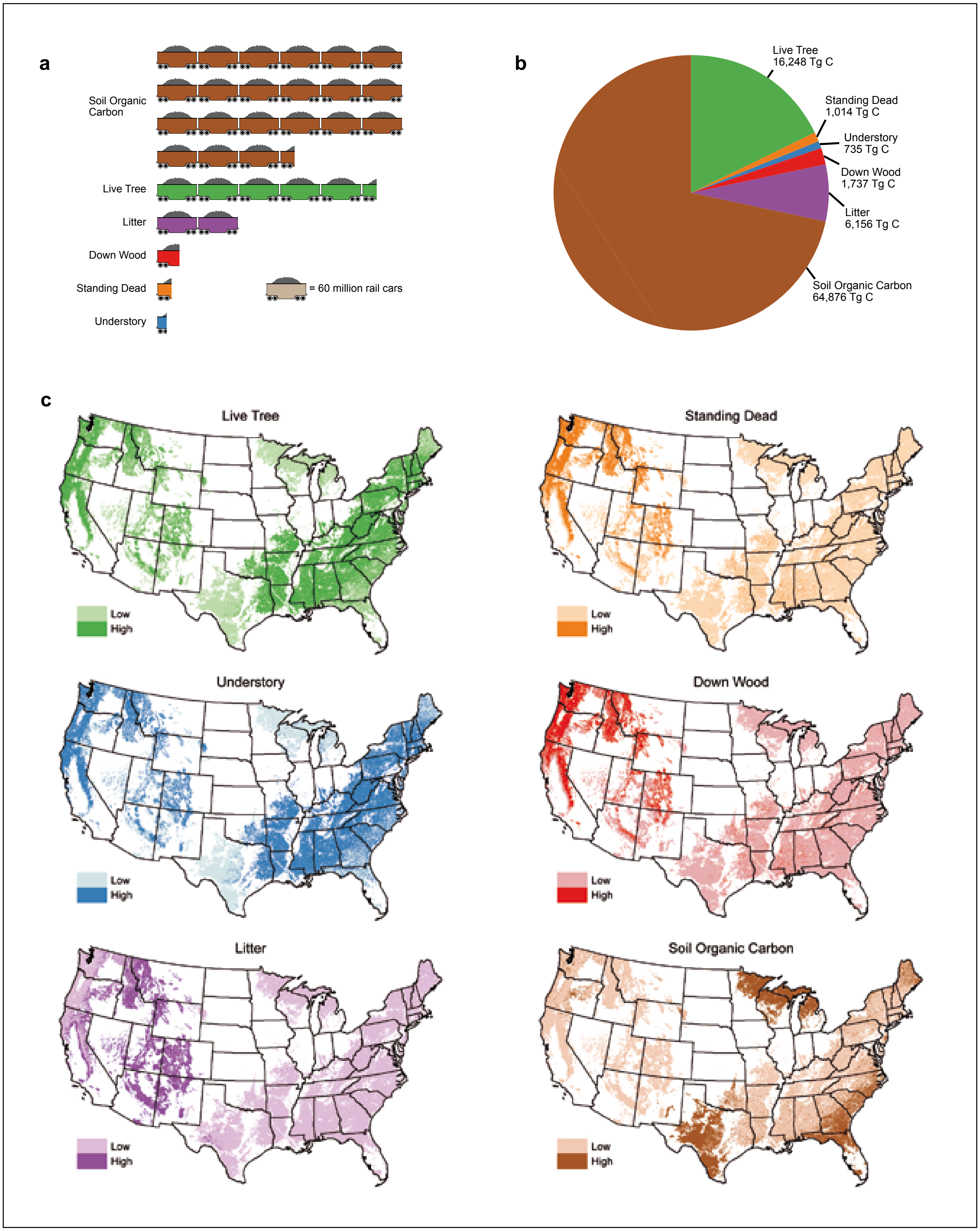


Figure 7.—Coal equivalents (a) and proportion of forest carbon stocks by pool (b) along with preponderance maps (c) by pool across the conterminous United States. Note: Pool preponderance maps from Wilson et al. (2013) will eventually be updated per emerging pool estimation techniques (e.g., Domke et al, in review).

Change in Forest Stocks by Pool

In the period from 1990 to 2016, the most dynamic forest carbon pools included those most closely associated with tree growth, removals, and mortality: live, standing dead, and downed dead trees. However, not all net carbon sequestration occurs in forests remaining forests across the reporting period as there is net accumulation of forest, and hence, the movement of carbon from other land uses and pools into forests. As a case study, Woodall et al. (2015) examined the movement of carbon from pools in other land uses to forests for the eastern United States over the period 2000 to 2012 (Fig. 8). For the soil organic carbon pool, more than 60 percent of carbon accumulation resulted from net positive carbon transfer into forests from other land uses (e.g., agriculture or developed). In contrast, for the aboveground live tree carbon pool only ~18 percent of carbon accumulation resulted from net land use transfers.

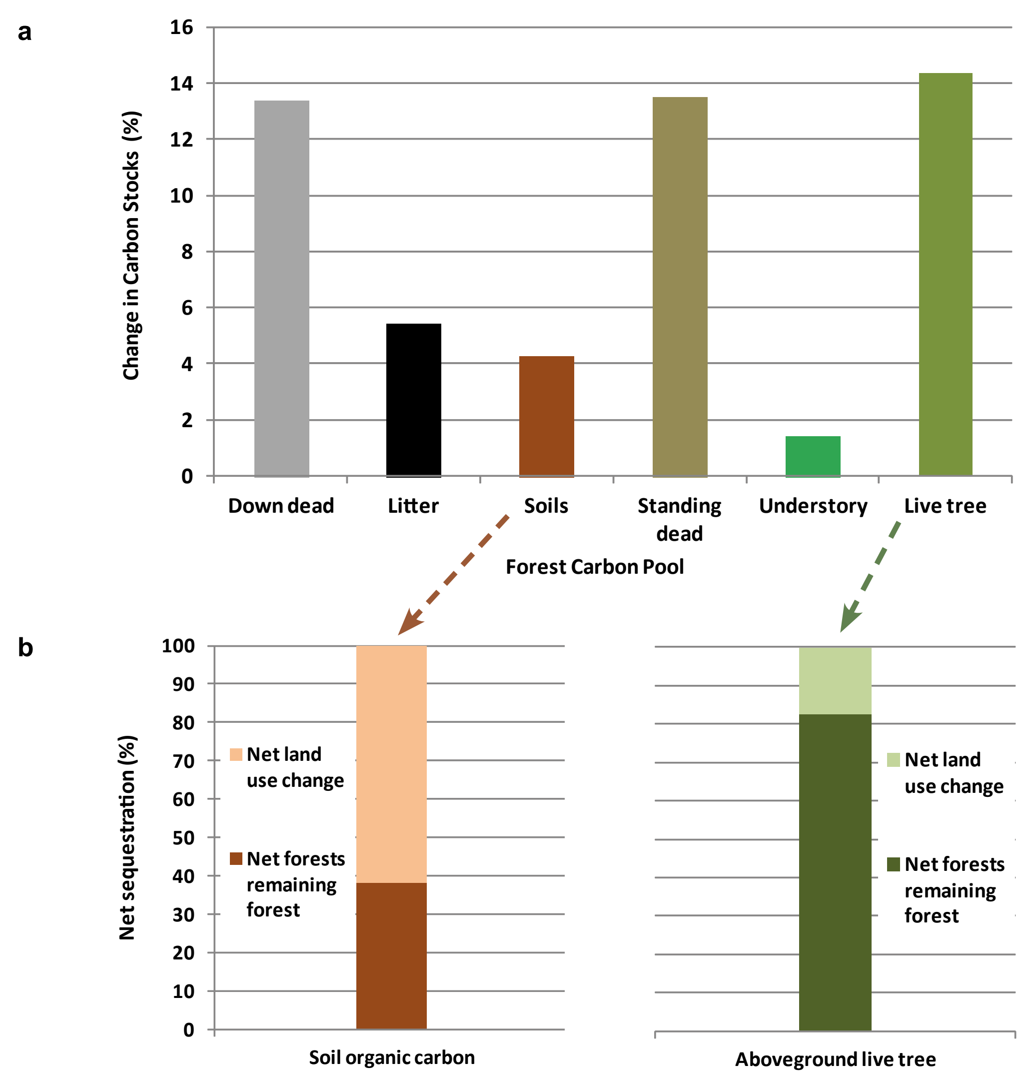


Figure 8.—FCAF results for changes in forest carbon stocks by pool from 1990-2016 in managed U.S. forests (a), and a case study examination (b) of land use change and carbon accretion for the two largest stocks, soil organic carbon and aboveground live trees, in eastern U.S. forests, 2000-2012 (Woodall et al. 2015).

CARBON STOCKS AND STOCK CHANGE

Regional Forest Carbon Estimates

Forest carbon stocks increased across all regions of the United States (Fig. 9). In forests that remained forest, carbon accumulation from net forest growth resulted in a net annual accumulation in all regions. Trends in net forest growth were variable across the baseline period, with the North, South, and Pacific Coast regions demonstrating an increasing rate of net forest growth while the Rocky Mountain region had a decreasing (but still positive) rate of carbon accumulation. Due to the availability of remeasured annual plots in the eastern United States, there is greater resolution of the effects of land use change, with the effect of net transfers of land into forest representing a portion of the total sink nearly equal to that of net forest growth. In this documentation, general assumptions about rates of land use change in western states were adopted based on initial results from examining split annual inventory cycles (see Methods section on page 16). If resources permit continued remeasurement of annual plots in the western United States, then FCAF outputs can refine these regional land use baselines in the future as remeasured data become available.

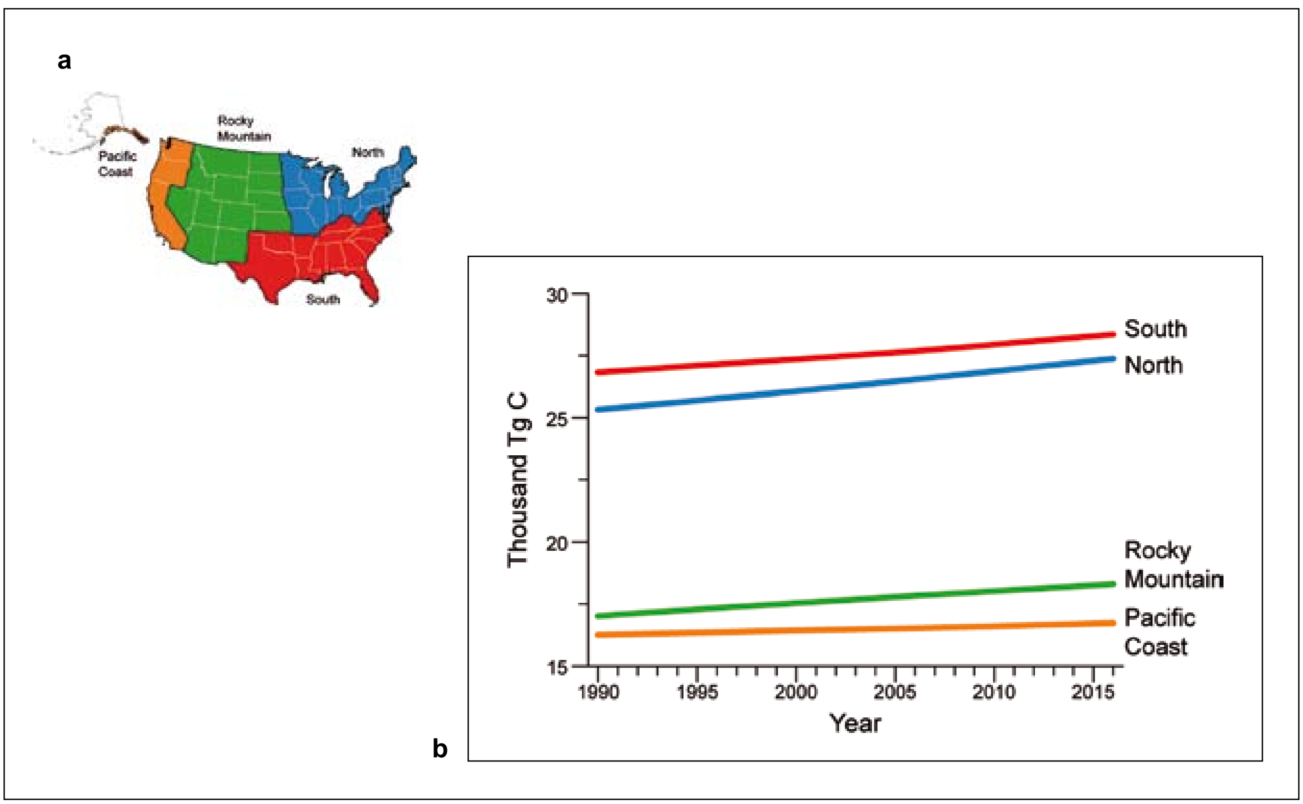


Figure 9.—Regional disaggregation of forest carbon analysis, 1990-2016: (a) regional delineations, (b) U.S. forest carbon stocks, and (c) annual forest carbon flux delineated by forests remaining forest (net forest carbon accretion) and land use change (net carbon transfer into forest land use) by region.

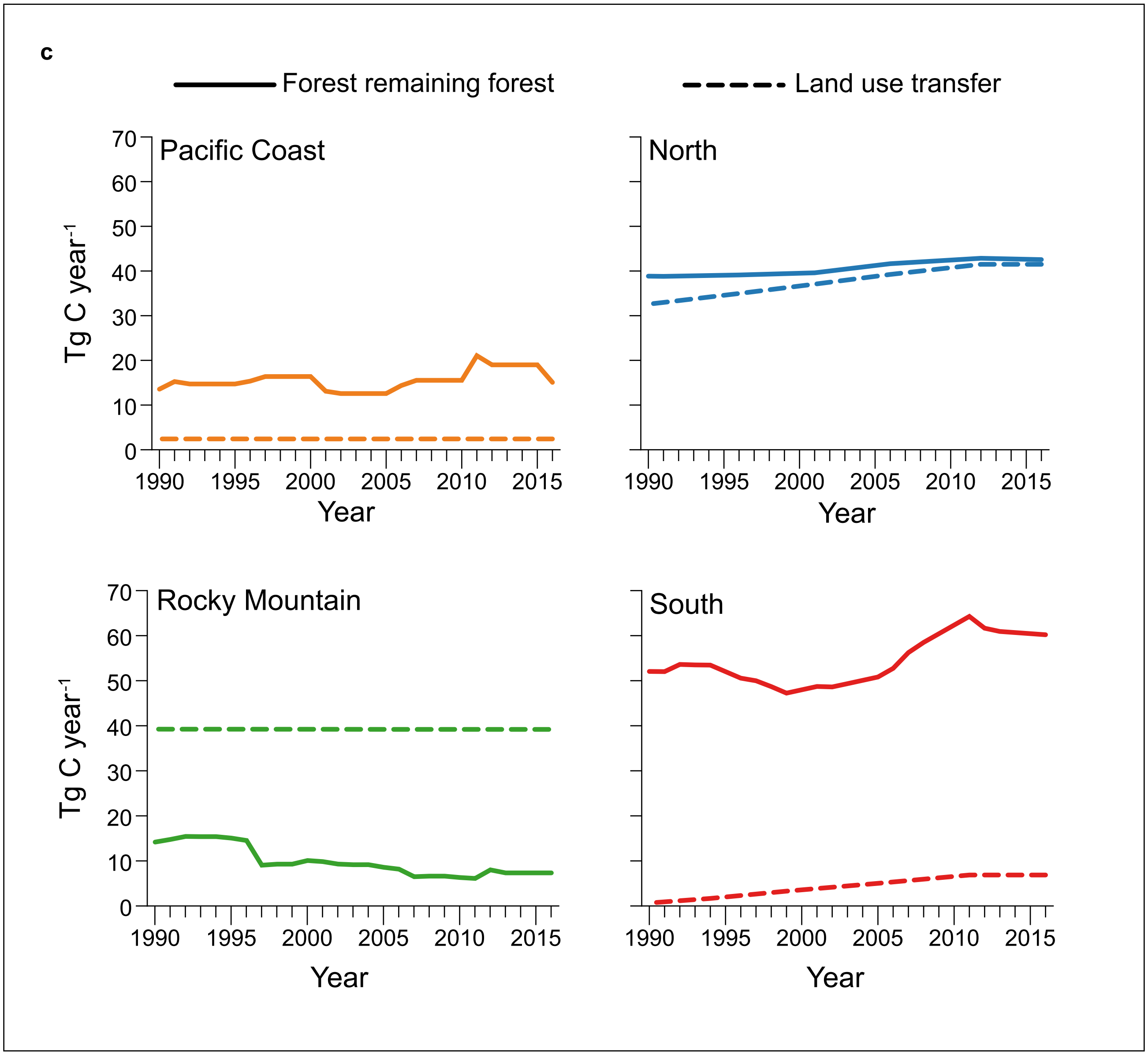


Figure 9 (continued).—Regional disaggregation of forest carbon analysis, 1990-2016: (a) regional delineations, (b) U.S. forest carbon stocks, and (c) annual forest carbon flux delineated by forests remaining forest (net forest carbon accretion) and land use change (net carbon transfer into forest land use) by region.

National Forest Carbon Estimates

Since 1990, forests in the United States have contributed from 194.4 to 224.5 Tg C·yr $^{-1}$ toward the net sequestration of atmospheric carbon (Table 1). Net land use change (nonforest converted to forest after subtracting forest converted to nonforest) accounted for a substantial portion of net sequestration although forest growth (i.e., growth in forest remaining forest) continued to be the major component of net sequestration. The total U.S. forest carbon stock was tremendous at over 90,000 Tg C (Table 2).

Table 1.—Annual carbon flux (Tg C·yr $^{-1}$) by net land use change, forests remaining forest, and total net sequestration in managed U.S. forests, 1990-2016. Positive values indicate carbon removal from the atmosphere.

Year	Net land use change	Forests remaining forest	Net sequestration
1990	75.2	119.2	194.4
1991	75.8	121.4	197.2
1992	76.4	123.2	199.6
1993	77.1	123.1	200.2
1994	77.7	123.1	200.9
1995	78.5	121.4	199.9
1996	79.2	120.1	199.3
1997	79.9	115.2	195.1
1998	80.7	114.2	194.9
1999	81.4	112.9	194.3
2000	82.1	114.5	196.6
2001	82.8	111.8	194.6
2002	83.5	111.1	194.6
2003	84.2	112.0	196.3
2004	85.0	113.2	198.2
2005	85.7	113.8	199.4
2006	86.4	117.5	203.9
2007	87.1	120.7	207.8
2008	87.8	123.3	211.1
2009	88.5	125.4	213.9
2010	89.2	127.2	216.4
2011	89.9	134.6	224.5
2012	90.2	132.1	222.3
2013	90.2	130.6	220.8
2014	90.2	130.3	220.5
2015	90.2	130.0	220.2
2016	90.2	125.7	216.0

Table 2.—Forest carbon stocks (Tg C) by pool and year in managed U.S. forests, 1990-2016

Year	Downed dead wood[a]	Litter	Soil organic carbon	Standing dead[a]	Understory[a]	Live trees[a]	Total ecosystem stocks
1990	1,532.0	5,839.2	62,230.3	893.2	725.4	14,208.1	85,428.0
1991	1,538.9	5,852.2	62,323.5	895.9	725.3	14,289.4	85,625.2
1992	1,546.0	5,865.2	62,418.8	898.8	725.2	14,370.8	85,824.8
1993	1,553.2	5,878.2	62,514.5	901.7	725.2	14,452.2	86,025.0
1994	1,560.4	5,891.2	62,610.7	904.8	725.1	14,533.7	86,225.9
1995	1,567.7	5,904.2	62,707.3	907.8	725.1	14,613.7	86,425.8
1996	1,575.0	5,917.0	62,801.2	911.5	725.1	14,695.2	86,625.1
1997	1,582.7	5,928.6	62,897.9	917.5	725.5	14,768.1	86,820.2
1998	1,590.3	5,940.0	62,995.6	923.6	725.8	14,839.6	87,015.1
1999	1,598.0	5,951.5	63,094.0	929.8	726.3	14,909.9	87,209.4
2000	1,605.7	5,963.1	63,193.8	936.2	726.7	14,980.6	87,406.0
2001	1,612.9	5,973.5	63,300.2	942.3	727.6	15,044.1	87,600.6
2002	1,619.9	5,984.4	63,407.0	945.8	728.5	15,109.6	87,795.2
2003	1,627.1	5,995.4	63,514.3	949.3	729.4	15,176.0	87,991.5
2004	1,634.3	6,006.6	63,622.3	952.9	730.3	15,243.3	88,189.6
2005	1,641.6	6,017.9	63,730.8	956.1	731.2	15,311.5	88,389.1
2006	1,649.9	6,029.6	63,828.6	960.1	731.5	15,393.2	88,593.0
2007	1,658.1	6,041.2	63,929.7	964.9	731.9	15,474.8	88,800.8
2008	1,666.3	6,053.1	64,031.7	969.8	732.3	15,558.6	89,011.8
2009	1,674.7	6,065.1	64,134.5	974.7	732.7	15,644.0	89,225.7
2010	1,683.1	6,077.1	64,238.3	979.7	733.1	15,730.6	89,442.1
2011	1,692.1	6,090.7	64,345.9	984.9	733.4	15,819.6	89,666.6
2012	1,701.1	6,104.1	64,451.2	990.7	733.8	15,908.0	89,888.9
2013	1,710.1	6,117.3	64,556.6	996.7	734.1	15,994.8	90,109.7
2014	1,719.2	6,130.5	64,662.1	1,002.7	734.5	16,081.2	90,330.2
2015	1,728.4	6,143.6	64,767.6	1,008.7	734.9	16,167.3	90,550.4
2016	1,748.1	6,218.4	65,244.3	1,017.4	739.5	16,294.5	91,262.1

[a] Includes aboveground and belowground components.

METHODS AND DATA SOURCES

FCAF Technical Specifications

Overview

The FCAF is fundamentally driven by the annual forest inventory system conducted by the Forest Inventory and Analysis program of the U.S. Forest Service (2014d, 2015a). The FIA program is considered to be the National Forest Inventory (NFI) for the United States, so these terms are used interchangeably. The FCAF system is comprised of a forest dynamics module and a land use dynamics module. The forest dynamics module assesses forest sequestration, forest aging, and disturbance effects (i.e., disturbances such as wind, fire, and floods identified by foresters on inventory plots). The land use dynamics module assesses carbon stock transfers associated with afforestation and deforestation. Both modules are developed from land use area statistics and carbon stock change or carbon stock transfer by age class. The required inputs are estimated from more than 625,000 forest and nonforest observations in the FIA national database (U.S. Forest Service 2014a, b, c). Model predictions for before or after the annual inventory period are constructed from the FCAF system using the annual observations. This modeling framework includes opportunities for user-defined scenarios to evaluate the impacts of land use change and disturbance rates on future carbon stocks and stock changes. The accounting system is flexible and can incorporate emerging inventory data (e.g., remeasured western plots and Alaskan lichen biomass), future image-based change estimation information (see Planned Improvements section on page 28), data from trends in burn severity (Eidenshink et al. 2007), and process model output (i.e., inform future forest carbon densities or land use dynamics). The future accounting system will be transparent and verifiable through open-source, publicly available R software that links with the FIA database and associated distillations. The accounting system is scalable to allow other users to parameterize models at scales relevant to them, but inherently the framework is built for application at the strategic scale, using FIA data to parameterize the matrices. This introduction to the FCAF is just the first step in a process to engage the public and policy makers in interpreting forest carbon status and trends. Whether it is remeasuring western inventory plots, initiating an inventory of interior Alaska, or vetting emerging research, we expect years of refinements to the FCAF.

Data

Data from the FIA program are the basis for the FCAF and the U.S. forest carbon inventory program (U.S. Forest Service 2014a). The FIA program relies on a rotating panel statistical design with a sampling intensity of one 674.5 m^2 ground plot per 2,403 ha of land and water area. A multi-panel design, with a percentage of all field plots systematically distributed and measured each year within each panel, is used with a base federal measurement period of 7 years (i.e., 7 panels) in eastern states and 10 years (i.e., 10 panels) in western states. The interpenetrating hexagonal design across the U.S. landscape enables the sampling of plots at various intensities in a spatially and temporally unbiased manner. Typically, tree and site attributes are measured with a higher sample intensity while other ecosystem attributes such as downed dead wood are sampled during summer months at lower intensities. From the measurements taken on the field plots, carbon estimates are predicted for six pools: live trees (aboveground and belowground), understory vegetation, standing dead trees, downed dead wood, litter, and soil organic carbon. The techniques for estimating these pools are detailed in the recent

National Greenhouse Gas Inventory annexes (USEPA 2015b). An important refinement of these techniques is the adoption of a new approach (Domke et al., in prep.) for estimating soil organic carbon, whose preliminary results are included in this assessment.

Carbon in Soil Organic Matter

Soil organic carbon (SOC) is the largest terrestrial carbon sink, and management of this pool is a critical component of efforts to mitigate atmospheric carbon concentrations. Soil organic carbon also affects essential biological, chemical, and physical soil functions such as nutrient cycling, water retention, and soil structure (Jandl et al. 2014). Much of the SOC on earth is found in forest ecosystems and is thought to be relatively stable. However, there is growing evidence that SOC is sensitive to global change effects, particularly land use histories, resource management, and climate. Given the cost and time required to measure SOC, and particularly changes in SOC, many of the UNFCCC signatory nations report estimates of SOC stocks and stock changes using default values from the Intergovernmental Panel on Climate Change or country-specific models (Keith et al. 2009, Kurz and Apps 2006). Country-specific models are often developed from soil inventories that are not representative of all land uses and vegetation types, resulting in unquantified uncertainties. In the United States, SOC in forests is monitored by the national forest inventory conducted by the FIA program (O'Neill et al. 2005). The FIA program currently uses SOC predictions based, in part, on a model using the Soil Survey Geographic (SSURGO) and the State Soil Geographic (STATSGO) databases compiled by the Natural Resources Conservation Service (NRCS) (Amichev and Glabraith 2004), hereafter referred to as the country-specific (CS_{soc}) model. Most estimates of forest SOC found in the SSURGO and STATSGO databases are based primarily on expert opinion and lack systematic field observations, but these country-specific model predictions have been used in past UNFCCC reporting (USEPA 2015a, b). The FIA program has been consistently measuring soil attributes as part of the inventory since 2001 and has amassed an extensive inventory of SOC in forest land in the conterminous United States and coastal Alaska (O'Neill et al. 2005). More than 5,000 profile observations of SOC on forest land from FIA and the International Soil Carbon Monitoring Network were used to develop and implement a modeling framework used for UNFCCC reporting that includes site-, stand-, and climate-specific variables that yield predictions of SOC stocks and stock changes specific to forest land in the United States. This section provides a summary of the methodology used to predict SOC for this report. A complete description of the approach is given in Domke et al. (in prep.).

The data used to develop the new modeling framework to predict SOC on forest land came from the FIA program and the ISCN. Since 2001, the FIA program has collected soil samples on every 16th base intensity plot distributed approximately every 38,848 ha, where at least one forested condition exists (Woodall et al. 2011a). On fully forested plots, mineral and organic soils were sampled adjacent to subplots 2, 3, and 4 by taking a single core at each location from two layers: 0 to 10.16 cm and 10.16 to 20.32 cm. The texture of each soil layer was estimated in the field, and physical and chemical properties were determined in the laboratory (U.S. Forest Service 2011). For this analysis, estimates of SOC from the FIA program were calculated following O'Neill et al. (2005):

$$\sum SOC_{FIA\_TOTAL} = C_i \cdot BD_i \cdot t_i \cdot ucf \qquad (1)$$

Where

$\sum SOC_{FIA\_TOTAL}$ = total mass (Mg C ha^{-1}) of the mineral and organic soil carbon over all ith layers,

C_i = percent organic carbon in the ith layer,

BD_i = bulk density calculated as weight per unit volume of soil (g·cm^{-3}) at the ith soil layer,

t_i = thickness (cm) of the ith soil layer (either 0 to 10.16 cm or 10.16 to 20.32 cm), and

ucf = unit conversion factor (100).

The SOC_{FIA_TOTAL} estimates from each plot were assigned and averaged by forest condition, resulting in 3,667 profiles with SOC layer observations at 0 to 10.16 and 10.16 to 20.32 cm depths. Since the United States has historically reported SOC estimates to a depth of 100 cm (USEPA 2015a), ISCN data from forests in the United States were harmonized with the FIA soil layer observations to develop models of SOC by soil order to a depth of 100 cm. All observations used from the ISCN were contributed by the Natural Resources Conservation Service. A total of 16,504 soil layers from 2,037 profiles were used from ISCN land uses defined as deciduous, evergreen, or mixed forest. The FIA-ISCN harmonized dataset used for model selection and prediction included a total of 5,704 profiles with 23,838 layer observations at depths ranging from 0 to 1,148 cm.

The modeling framework developed to predict SOC for this report was built around strategic-level forest and soil inventory information and auxiliary variables available for all FIA plots in the United States. The first phase of the new estimation approach involved fitting models using the midpoint of each soil layer from the harmonized dataset and SOC estimates at those midpoints. Several linear and nonlinear models were evaluated, and a log-log function provided the optimal fit to the harmonized data:

$$\log_{10} SOC_i = I + \log_{10} Depth \qquad (2)$$

Where

$\log_{10} SOC_i$ = SOC density (Mg C ha^{-1} cm depth^{-1}) at the midpoint depth,

I = intercept, and

$\log_{10} Depth$ = profile midpoint depth (cm).

The model was validated by partitioning the complete harmonized dataset multiple times into training and testing groups and then repeating this step for each soil order to evaluate model performance by soil order. Extra sum of squares F tests were used to evaluate whether there were statistically significant differences between the model coefficients from the model fit to the complete harmonized dataset and models fit to subsets of the data by soil order. Model coefficients for each soil order were used to predict SOC for the 20.32 to 100 cm layer for all FIA plots with soil profile observations. Next, the SOC layer observations from the FIA and predictions over the 100 cm profile for each FIA plot were summed:

$$SOC_{100} = SOC_{FIA\_TOTAL} + SOC_{20\text{-}100} \qquad (3)$$

Where

SOC_{100} = total estimated SOC density from 0-100 cm for each forest condition with a soil sample in the FIA database,

SOC_{FIA_TOTAL} = as defined in model (1), and

$SOC_{20\text{-}100}$ = predicted SOC from 20.32 to 100 cm from model (2).

Note that bias correction factors will be incorporated into the $SOC_{20\text{-}100}$ predictions and evaluated in Domke et al. (in prep.) but were not included in the SOC_{100} estimates used in this analysis.

In the second phase of the modeling framework, SOC_{100} estimates for FIA plots were used to predict SOC for plots lacking SOC_{100} estimates using Random Forests (RF), a machine learning tool that uses bootstrap aggregating (i.e., bagging) to develop models to improve prediction (Breiman 2001). Random Forests also relies on random variable selection to develop a forest of uncorrelated regression trees. These trees recognize the relationship between a dependent variable, in this case SOC_{100}, and a set of predictor variables. All relevant predictor variables—those that may influence the formation, accumulation, and loss of SOC—from annual inventories collected on all base intensity plots and auxiliary climate, soil, and topographic variables obtained from the PRISM climate group (Northwest Alliance 2015), Natural Resources Conservation Service (NRCS

2015), and U.S. Geological Survey (Danielson and Gesch 2011), respectively, were included in the RF analysis. Due to regional differences in sampling protocols, many of the predictor variables included in the RF variable selection process were not available for all base intensity plots. To avoid problems with data limitations, pruning was used to reduce the RF models to the minimum number of relevant predictors (including both continuous and categorical variables) without substantial loss in explanatory power or increase in root mean squared error (RMSE). The general form of the full RF models were:

$$P(SOC) = f\,(lat, lon, elev, fortypgrp, ppt, t\max, gmi, order, surfgeo) + u \qquad (4)$$

where *lat* = latitude, *lon* = longitude, *elev* = elevation, *fortypgrp* = forest type group, *ppt* = mean annual precipitation, *t*max = average maximum temperature, *gmi* = the ratio of precipitation to potential evapotranspiration, *order* = soil order, *surfgeo* = surficial geological description, and *u* = the uncertainty in the prediction resulting from the sample-based estimates of the model parameters and observed residual variability around this prediction. For each replacement, *u* was independently and randomly generated from a N(0,σ) distribution, with σ incorporating the variability from both sources. This process of randomly selecting and incorporating *u* may be considered an imputation. Each model prediction was replaced independently *m* times, and *m* separate estimates were combined following Rubin (1987):

$$\hat{\hat{C}} = \frac{1}{m}\sum_{k=1}\hat{C}^{k} \qquad (5)$$

where $\hat{\hat{C}}$ is the estimate for the *k*th completion of the dataset. In this analysis, *m* = 1,000, which is markedly larger than the *m* recommended by Rubin (1987), but given the extremely high level of replacement in this study, it was deemed necessary (Bodner 2008).

The FIA dataset used to develop the full RF model was partitioned multiple times into training and testing groups, and the results were evaluated graphically and with a variety of statistical metrics, including RMSE and modeling efficiency (*EF*). This provided an index of model performance on a relative scale where 1 indicated a perfect fit, 0 suggested the model was no better than the mean, and negative values indicated a poor model fit. The RMSE for the full model was 32.78 Mg C ha^{-1} and the *EF* was 0.36. The RF predictions from the full model were also evaluated against the SOC_{100} estimates using an equivalence testing framework (Wellek 2003). This method assumes the values are not equivalent unless the *P*(*SOC*) predictions and SOC_{100} estimates demonstrate they are similar to within a predefined tolerance. A region of indifference was defined as ±25 percent, meaning the absolute value of the mean of the difference is less than 25 percent of the standard deviation. The SOC_{100} estimates and *P*(*SOC*) predictions were statistically equivalent with a mean difference of 0.95 (standard deviation = ±15.53) Mg C ha^{-1}. The *P*(*SOC*) predictions represent an estimated 40 percent (42.52 ± 46.80 Mg C ha^{-1}) increase in carbon stocks per unit area relative to the county-specific predictions which have been used in previous UNFCCC reports. As a final step in this analysis, the *P*(*SOC*) predictions were compared to SOC estimates published in the recent literature. The *P*(*SOC*) predictions ranged from 47.90 to 374.57 Mg C ha^{-1} with a mean of 105.40 Mg C ha^{-1}. These predictions are consistent with estimates from studies across forest types of the United States (Jobbagy and Jackson 2000, Lal 2005, Sun et al. 2004, Tan et al. 2004, Thompson and Kolka 2005, Woldeselassie et al. 2012) and with estimates obtained from a large scale soil survey in European forests (De Vos et al. 2015).

Estimation of Other Pools

Techniques for estimating the carbon stocks of all other pools (other than SOC) are identical to those used in the previous NGHGI (USEPA 2015b). Briefly, forest inventory data are converted to carbon units or augmented by other ecological data. Expansion factors are applied to the survey data at the scale of FIA inventory plots. The results are estimates of carbon density (Mg C ha^{-1}) for the various forest pools. Carbon density for live trees, standing dead trees, understory vegetation, downed dead wood, litter, and soil organic matter are estimated. All nonsoil pools except litter can be separated into aboveground and belowground components. The live tree and understory carbon pools have been pooled as biomass in the greenhouse gas inventory. Similarly, standing dead trees and downed dead wood have been pooled as dead wood. Regardless of the pool delineations used in this initial report, they can be summarized in various ways for varying reporting formats.

- **Live trees**—Live tree carbon pools include aboveground and belowground (coarse root) biomass of live trees with diameter at breast height of at least 2.54 cm at 1.37 m above the forest floor. Separate estimates are made for aboveground and belowground biomass components. If inventory plots include data on individual trees, tree carbon is based on Woodall et al. (2011b) using the component ratio method (CRM), which is a function of volume, species, diameter, and, in some regions, tree height and site quality. The estimated sound volume (i.e., after rotten and missing tree volume have been deducted) provided in the tree table of the FIA database is the principal input to the CRM biomass calculation for each tree (Woodall et al. 2011b). The estimated volumes of wood and bark are converted to biomass based on the density of each. Additional components of the trees, such as tops, branches, and coarse roots, are estimated according to adjusted component estimates from Jenkins et al. (2003). Live trees with a d.b.h. of less than 12.7 cm do not have estimates of sound volume in the FIA database, and CRM biomass estimates follow a separate process (see Woodall et al. 2011b for details). An additional component of foliage, which is not explicitly included in Woodall et al. (2011b), was added to each tree following the same CRM method. Carbon was estimated by multiplying the estimated oven-dry biomass by a carbon constant of 0.5 because carbon is 50 percent of dry weight (IPCC 2006). Further discussion and example calculations are provided in Woodall et al. (2011b) and Domke et al. (2012).
- **Understory vegetation**—Understory vegetation is a minor component of total forest ecosystem biomass. Understory vegetation is defined as all biomass of undergrowth plants in a forest, including woody shrubs and trees less than 2.5-cm d.b.h. Estimates of carbon density are based on Birdsey (1996), and calculation details are provided by the U.S. Environmental Protection Agency (2015b). The approach to quantifying carbon in this pool is expected to be revised in the near future.
- **Standing dead trees**—The standing dead tree estimates are primarily based on plot-level measurements (Domke et al. 2011, Woodall et al. 2012). This carbon pool includes aboveground and belowground (coarse root) mass and includes trees of at least 12.7-cm d.b.h. Calculations follow the basic CRM method applied to live trees (Woodall et al. 2011b) with additional modifications to account for decay and structural loss. In addition to the lack of foliage, two characteristics of standing dead trees that can substantially affect carbon mass are decay, which affects density and thus specific carbon content (Domke et al. 2011, Harmon et al. 2011), and structural loss such as missing branches and bark (Domke et al. 2011). Dry weight is converted to carbon mass by multiplying by 0.5.
- **Downed dead wood**—Downed dead wood, inclusive of logging residue, are sampled on a subset of FIA plots. Despite a reduced sampling intensity, empirical estimates of downed dead wood are used in combination with model predictions to compile a single downed woody material population estimate (Domke et al. 2013, Woodall et al. 2013) per state. Downed dead wood is defined as pieces of dead wood with a diameter greater than 7.5 cm at transect intersection, that are not attached to live or standing dead trees. It also includes stumps and roots of harvested trees.

Estimates for downed dead wood correspond to the region and forest type classifications described in Smith et al. (2003). An additional component of downed dead wood is a regional average estimate of logging residue based on Smith et al. (2006) applied at the plot level. These are based on a regional average carbon density at age zero and first order decay. These amounts are added to explicitly account for downed dead wood following harvest. The sum of these two components is then adjusted by the ratio of population totals; that is, the ratio of plot-based to modeled estimates (Domke et al. 2013). Details are provided in U.S. Environmental Protection Agency (2015b).

- **Litter**—Carbon in the litter layer is currently sampled on a subset of the FIA plots. Litter carbon is the pool of organic carbon (including material known as duff, humus, and fine woody debris) above the mineral soil and includes woody fragments with diameters of up to 7.5 cm. Because litter attributes are only collected on a subset of FIA plots, a model was developed to predict carbon density based on site-, stand-, and climate-specific variables from plots that lacked litter information (Domke et al., in review). Since the modeling framework used to obtain predictions of litter carbon is new this year, a more detailed overview of the methods is provided here, and a full description of the methods is described in Domke et al. (in review).

The first step in model development was to evaluate all relevant variables—those that may influence the formation, accumulation, and decay of litter organic matter—from annual inventories collected on base intensity plots. This was done using RF variable selection and litter carbon estimates from FIA plots (n = 4,553) where litter attributes were sampled from 2001-2012. Random Forests was used to evaluate the importance of all relevant predictor variables available on base intensity plots in the FIA. Due to regional differences in sampling protocols, many of the predictor variables included in the RF variable selection process were not available for all base intensity plots. To avoid problems with data limitations, pruning was used to reduce the RF models to the minimum number of relevant predictors (including both continuous and categorical variables) without substantial loss in explanatory power or increase in RMSE. The general form of the full RF models was:

$$P(Litter) = f\,(elev, lon, above, gmi, fortypgrp, ppt, t\text{max}, lat) + u \quad (6)$$

where $P(Litter)$ = litter carbon (Mg C ha^{-1}), *above* = aboveground live tree carbon (trees ≥ 2.54-cm d.b.h.), and other variables are as defined for model (4). For each replacement, *u* was independently and randomly generated from a N(0,σ) distribution with σ incorporating the variability from the sample-based estimates of the model parameters and observed residual variability around the predictions. Each model prediction was replaced independently *m* times, and *m* separate estimates were combined following Rubin (1987) using model (5).The FIA dataset used to develop the full RF model was partitioned multiple times into training and testing groups, and the results were evaluated graphically and with a variety of statistical metrics.

Attribution

Attribution is the separation of impacts of major disturbance from forest sequestration. In the eastern United States where remeasured data are available, this was done directly based on repeated observations (Coulston et al. 2015). In the western United States where only one measurement is available, a coarse-scale model was adopted (Coulston, in prep.). The coarse-scale model arises from a finer-scale model:

$$E(\delta C_{dp}) = E(C_{dp}) - E(C_{-dp}) \quad (7)$$

Where

$E(\ )$ is the expected value,

δC_{dp} is the change in carbon for plot *p* with disturbance *d*,

C_{dp} is the current carbon stock of plot *p* with disturbance *d*, and

C_{-dp} is the carbon stock for plot *p* without disturbance.

$E(C_{-dp})$ may be developed from a model such as:

$$E(C_{-dp}) = f(fortypgrp, C_{tree}, SD, SI...) \quad (8)$$

Where

C_{tree} = total live and standing dead tree carbon,

SD = stand density, and

SI = site index.

In simple terms this approach models δC_{dp} as the observed deviation from a carbon yield curve. However, the same general idea can be employed as a population model. Suppose that a disturbance or management activity occurs at random within a forest type (population). Under this assumption for each forest type:

$$E(\boldsymbol{\Delta C}_d) = F_d * (\boldsymbol{D}_d - \boldsymbol{D}_u) \quad (9)$$

Where

$\boldsymbol{\Delta C}_d$ = vector of population carbon change by pool associated with the disturbance,

F_d = area of the disturbance,

$\boldsymbol{D}_d$ = vector of carbon density (stock per unit area) by pool in disturbed areas, and

$\boldsymbol{D}_u$ = vector carbon density by pool in undisturbed areas.

The coarse-scale model was implemented for the western United States including west Texas and west Oklahoma. For fire disturbance $\mathbf{D}_{\mathrm{fire}}$ was compared to $\mathbf{D}_{\mathrm{u}}$ by forest type group. For cutting $\mathbf{D}_{\mathrm{cut}}$ was compared to $\mathbf{D}_{\mathrm{u}}$ by forest type group where $\mathbf{D}_{\mathrm{u}}$ was restricted to observations between ages 5 and 105. This age restriction was based on a small set of remeasurements for the western United States where 90+ percent of all observed cutting occurred in stands between 5 and 105. Note that cutting includes a range of cutting types from timber stand improvement to clearcutting.

Projections: Moving Annual Inventory Data Backward and Forward in Time

Wear and Coulston (2015) and Coulston et al. (2015) provide the framework for the projection model. The overall objective is to estimate unmeasured historical changes and future changes in forest carbon consistent with annual forest inventory measurements. For most regions, forest conditions are observed at time t_0 and at a subsequent time $t_1 = t_{0+s}$, where s is the time step (time measured in years) and is indexed by discrete (5 year) forest age classes. The inventory from t_0 is then backcasted to the year 1990 (on average about 16 years) and projected from t_1 to 2016 (about 5 years for the next inventory report). This backcasting/projection approach requires simulating changes in the age class distribution resulting from forest aging and disturbance events and then applying carbon density estimates for each age class. For the North, South (except for west Texas and west Oklahoma), and Rocky Mountains regions of the country, age class transition matrices are estimated from observed changes in age classes between t_0 and t_1. In the remainder of the regions (Pacific Coast including Alaska, west Texas, and west Oklahoma), only one inventory was available (t_0) so transition matrices were derived from theory but informed by the condition of the observed inventory to backcast from t_0 to 1990 and project from t_0 to 2016.

Theoretical Age Transition Matrices

Without any mortality-inducing disturbance, a projection of forest conditions would proceed by increasing all forest ages by the length of the time step until all forest resided in a terminal age class where the forest is retained indefinitely (this is by assumption, where forest carbon per unit area reaches a stable maximum). For the most basic case, disturbances (e.g., wildfire or timber harvesting) can reset some of the forest to the first age class. Disturbance can also alter the age class in more subtle ways. If a portion of trees in a multiple-age forest dies, the trees comprising the average age calculation change, thereby shifting the average age higher or lower (generally by one age class).

With n age classes, the age transition matrix ($\mathbf{T}$) is an n x n matrix, and each element ($\mathbf{T}_{qr}$) defines the proportion of forest area in class q transitioning to class r during the time step (s). The values of the elements of $\mathbf{T}$ depend on a number of factors, including forest disturbances such as harvests, fire, and storms, and the value of s, especially relative to the span of the age classes. For example, holding area fixed, allowing for no mortality, defining the time step s equivalent to the span of age classes, and defining five age classes results in:

$$\boldsymbol{T} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \end{pmatrix} \quad (10)$$

where all forest area progresses to the next age class and forests within the terminal age class are retained forever. With this version of **T**, after five time steps all forests would be in the terminal age class. Relaxing these assumptions changes the structure of **T**. If all disturbances, including harvesting and fire, that result in stand regeneration are accounted for and stochastic elements in forest aging are allowed, **T** defines a traditional Lefkovitch matrix population model (e.g., Caswell 2001) and becomes:

$$\boldsymbol{T} = \begin{pmatrix} 1-t_1-d_1 & d_2 & d_3 & d_4 & d_5 \\ t_1 & 1-t_2-d_2 & 0 & 0 & 0 \\ 0 & t_2 & 1-t_3-d_3 & 0 & 0 \\ 0 & 0 & t_3 & 1-t_4-d_4 & 0 \\ 0 & 0 & 0 & t_4 & 1-d_5 \end{pmatrix} \quad (11)$$

Where

t_q is the proportion of forest of age class q transitioning to age class $q + 1$,

d_q is the proportion of age class q that experiences a stand-replacing disturbance, and

$(1 - t_q - d_q)$ is the proportion retained within age class q ($\boldsymbol{T}_{qr}$).

Projections and Backcast for Pacific Coast, Rocky Mountains, West Texas, and West Oklahoma

Projections of forest carbon in the Pacific Coast region (including Alaska), Rocky Mountains, west Texas and west Oklahoma are based on a life stage model:

$$\Delta C_t = C_{(t+m)} - C_t = (\boldsymbol{F}_t\boldsymbol{T} - \boldsymbol{F}_t) \cdot \boldsymbol{Den} + \boldsymbol{L}_t \cdot \boldsymbol{Den} \quad (12)$$

In this framework **T** is an age transition matrix that shifts the age distribution of the forest **F**. The difference in forest area by age class between time t and $t+s$ is $\mathbf{F}_t\mathbf{T} - \mathbf{F}_t$. This quantity is multiplied by carbon density by age class (**Den**) to estimate carbon stock change of forest remaining forest between t and $t+s$. Land use change is accounted for by the addition of $\mathbf{L}_t \cdot \mathbf{Den}$, where $\mathbf{L}_t$ identifies the age distribution of net land shifts into or out of forests. A query of the forest inventory databases provides estimates of **F** and **Den**, while inventory observations and modeling assumptions are used to estimate **T**. By expanding **Den** to a matrix of carbon contained in all the constituent pools of forest carbon, projections for all pools are generated.

Land use change is incorporated as a 1 x n vector **L**, with positive entries indicating increased forest area and negative entries indicating loss of forest area, which provides insights of net change only. Implementing a forest area change requires some information and assumptions about the distribution of the change across age classes (the n dimension of **L**). In the eastern states, projections are based on the projection of observed gross area changes by age class. In western states, total forest area changes are applied using rules. When net gains are positive, the area is added to the youngest forest age class; when negative, area is subtracted from all age classes in proportion to the area in each age class category.

Backcasting forest carbon inventories generally involves the same concepts as forecasting. An initial age class distribution is shifted at regular time steps backward through time, using a transition matrix (**B**):

$$\boldsymbol{F}_{t-s} = \boldsymbol{F}_t \cdot \boldsymbol{B} \quad (13)$$

B is constructed based on similar logic used for creating **T**. The matrix cannot simply be derived as the inverse of **T** ($\mathbf{F}_{t-s} = \mathbf{F}_t\mathbf{T}^{-1}$) because of the accumulating final age class (i.e., **T** does not contain enough information to determine the proportion of the final age class derived from the n–1 age class and the proportion that is retained in age class n from the previous time step).[1] However, **B** can be constructed using observed changes from the inventory and assumptions about transition/accumulation including nonstationary elements of the transition model:

$$\boldsymbol{B} = \begin{pmatrix} 1-\sum_q d_q & b_2 & 0 & 0 & 0 \\ d_1 & 1-b_2 & b_3 & 0 & 0 \\ d_2 & 0 & 1-b_3 & b_4 & 0 \\ d_3 & 0 & 0 & 1-b_4 & b_T \\ d_4 & 0 & 0 & 0 & 1-b_T \end{pmatrix} \quad (14)$$

Forest area changes need to be accounted for in the backcasts as well:

$$\boldsymbol{F}_{t-s} = \boldsymbol{F}_t \boldsymbol{B} - \boldsymbol{L}_t \quad (15)$$

where $\mathbf{L}_t$ is the forest area change between t_1 and t_0 as previously defined.

In the Rocky Mountains, age class transition matrices were empirically derived from observed changes in age classes between t_0 and t_1. The frequency of transitions was constructed between age classes observed at t_0 and t_1 to define **T** and between age classes t_1 and t_0 to define **B**. In the Pacific Coast region, including Alaska, west Texas, and west Oklahoma, the theoretical life-stage models described by matrices 11 and 14 were applied. The disturbance factors (*d*) in both **T** and **B** are derived from the current inventory by assuming that the area of forest in age class 1 resulted from disturbance in the previous period, the area in age class 2 resulted from disturbance in the period before that, and so on. The source of disturbed forest was assumed to be proportional to the area of forest in each age class. For projections (**T**), the average of implied disturbance for the previous two periods was applied. For the backcast (**B**), we move the disturbance frequencies implied by the age class distribution for each time step. For areas with empirical transition matrices, change in forest area ($\mathbf{L}_t$) was backcasted/projected using the change in forest area observed for the period t_0 to t_1. In the Pacific Coast region, including Alaska, west Texas, and west Oklahoma, it was assumed that total forest land area remained constant for the time period examined.

[1] Simulation experiments show that a population that evolves as a function of **T** can be precisely backcast using $\mathbf{T}^{-1}$. However, applying the inverse to a population that is not consistent with the long run outcomes of the transition model can result in projections of negative areas within some stage classes.

Projections and Backcast for North, South, east Texas, and east Oklahoma

For the eastern United States a full set of remeasured plots were available. When remeasured data are available, the previously described approach is extended to estimate change more directly; in this case $\Delta\mathbf{C}_t = \mathbf{F}_t \cdot \boldsymbol{\delta}\mathbf{C}$ where $\Delta\mathbf{C}$ is net stock change by pool within the analysis area, **F** is as previously defined, and $\boldsymbol{\delta}\mathbf{C}$ is an n x cp matrix of per unit area forest carbon stock change per year by pool (cp) arrayed by forest age class. Inter-period forest carbon dynamics are previously described, and the age transition matrix (**T**) is estimated from the observed data directly. Forest carbon change at the end of the next period is defined as: $\Delta\mathbf{C}_{t+s} = \mathbf{F}_t \cdot \mathbf{T} \cdot \boldsymbol{\delta}\mathbf{C}$. Land use change and disturbances such as cutting, fire, weather, insects, and diseases were incorporated by generalizing to account for the change vectors and undisturbed forest remaining as undisturbed forest:

$$\Delta\boldsymbol{C}_{t+s} = \sum_{d \in L} (\boldsymbol{A}_{td} \cdot \boldsymbol{T}_d \cdot \boldsymbol{\delta C}_d) \quad (16)$$

Where

$\boldsymbol{A}_{td}$ = area by age class of each mutually exclusive land category in **L** which includes *d* disturbances at time *t*.

L = (FF, NFF, FNF, F_{cut}, F_{fire}, $F_{weather}$, F_{id}) where FF = undisturbed forest remaining as undisturbed forest, NFF = nonforest to forest conversion, FNF = forest to nonforest conversion, F_{cut} = cut forest remaining as forest, F_{fire} = forest remaining as forest disturbed by fire, $F_{weather}$ = forest remaining as forest disturbed by weather, and F_{id} = forest remaining as forest disturbed by insects and diseases.

In the case of land transfers (FNF and NFF), $\mathbf{T}_d$ is an n x n identity matrix and $\boldsymbol{\delta}\mathbf{C}_d$ is a carbon stock transfer rate by age. Paired measurements for all plots in the inventory provide direct estimates of all elements of $\boldsymbol{\delta}\mathbf{C}_d$, $\mathbf{T}_d$, and $\mathbf{A}_{td}$ matrices.

Projections are developed by specifying either $\mathbf{F}_{t+s}$ or $\mathbf{A}_{t+sd}$ for either a future or a past state. To move the system forward, **T** is specified so that the age transition probabilities are set up as the probability between a time 0 and a time 1 transition. To move the system backward, **T** is replaced by **B** so that the age transition probabilities are for transitions from time 1 to time 0. Forecasts were developed by assuming the observed land use transitions and disturbance rates would continue for the next 5 years. Backcasts were developed using a Markov Chain process for land use transitions, observed disturbance rates for fire, weather, and insects. Historical forest cutting was incorporated by using the relationship between the area of forest cutting estimated from the inventory plots and the volume of roundwood production from the Timber Products Output program (U.S. Forest Service 2014d). This relationship allowed for the modification of F_{cut} such that it followed trends described by Oswalt et al. (2014).

Total Uncertainty

There are many input variables (e.g., aboveground live biomass, forest land area) in the FCAF (Fig. 10) and each input variable has uncertainty. Techniques to account for the total uncertainty associated with the FCAF output (i.e., annual C flux in Table 1) are still under development. As a first approximation we intend to use a Monte Carlo-based framework. Uncertainty parameters (e.g., distribution functions and variance) that best reflect the potential errors associated with each input variable will be defined. For each input variable, many realizations (e.g., n_{mc} = 10,000) will be randomly generated using the uncertainty parameters. The realizations for each input variable will then be used in the FCAF to produce a distribution of predictions, means, and standard deviations for the annual C flux.

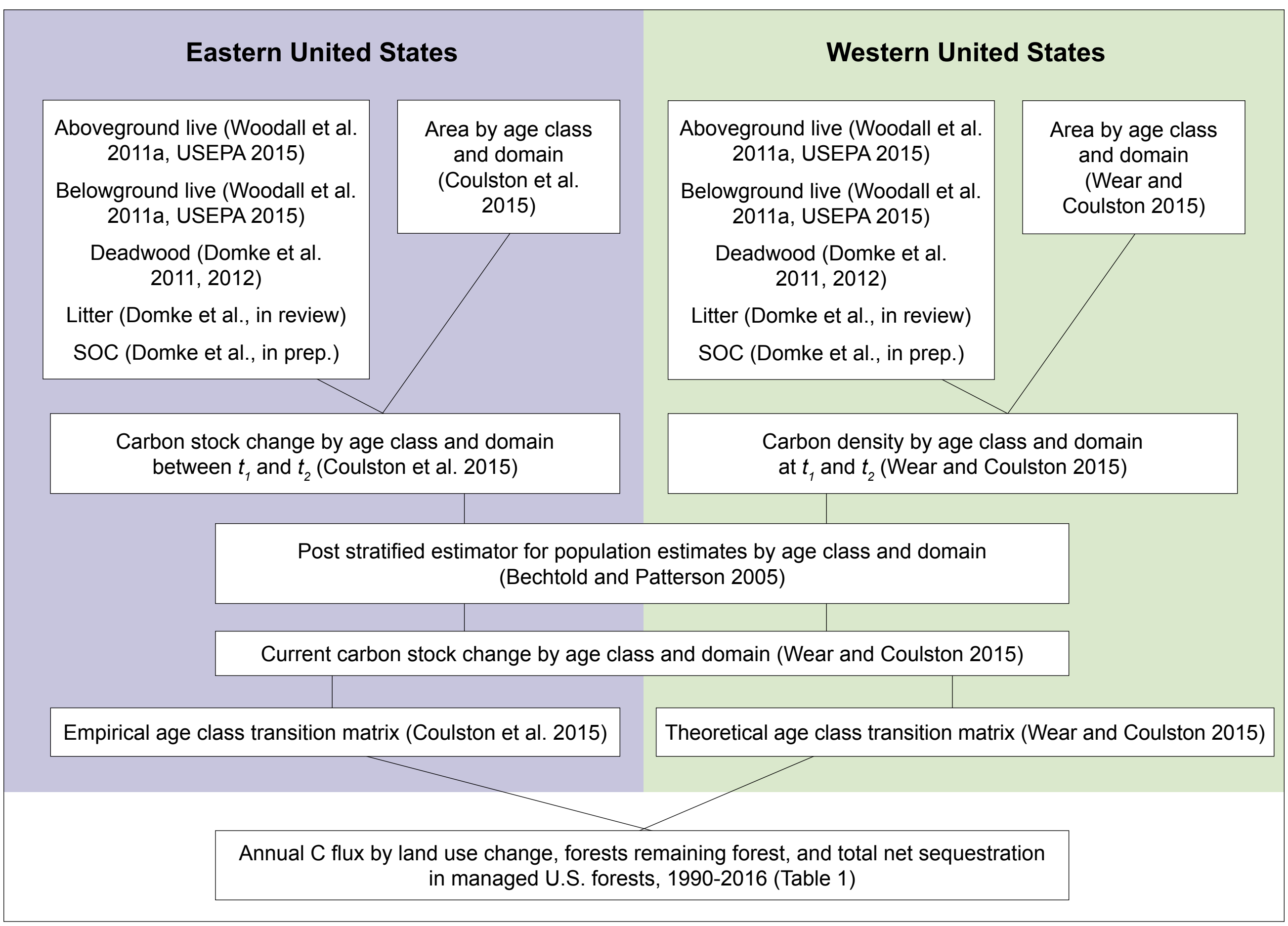


Figure 10.—Conceptual flowchart of the FCAF outlining the first approximation that is intended to measure total uncertainty for annual C flux predictions in the United States. Sources of uncertainty (with references) represent input variables that will be included in the total uncertainty assessment.

Annual Data Description

Contrary to past greenhouse gas inventories, periodic data were not used in the FCAF to develop national carbon baselines, instead we relied solely on annual FIA data (Tables 3 and 4). Annual FIA plots are consistently located across the United States in a spatially balanced and unbiased manner (Fig. 11). The base intensity of FIA plots is approximately one plot for every 2,428 ha. Strategic partners, such as states, have the opportunity to increase the base intensity by adding plots through direct or in-kind contributions. Some of these added plots may be established and measured at one point in time but are then not subsequently remeasured. The FIA database is structured such that statistically valid samples of change can be derived owing to the hexagonal and panelized system across the United States (see Bechtold and Patterson 2005). The attribution and projection system of FCAF will be greatly improved once western annual plots are remeasured in the years ahead.

Table 3.—Inventory data used to develop forest carbon estimates presented in this report by state and time (time 1 and time 2) for states with remeasured annual plots. Valid population estimates were made using the two independent measurement cycles (otherwise known as evaluations, see U.S. Forest Service 2014a, b).

Remeasured annual plots		
State	**Time 1 year range**	**Time 2 year range**
Alabama	2001 - 2009	2006 - 2014
Arkansas	2000, 2002, 2004 - 2010	2009 - 2014
Connecticut	2004 - 2008	2009 - 2013
Delaware	2004 - 2008	2009 - 2013
Florida	2002 - 2004, 2006 - 2007	2009 - 2013
Georgia	1998 - 2009	2005 - 2007, 2009 - 2013
Illinois	2004 - 2009	2009 - 2014
Indiana	2004 - 2008	2009 - 2013
Iowa	2004 - 2009	2009 - 2014
Kansas	2004 - 2009	2009 - 2014
Kentucky	2000 - 2009	2005 - 2006, 2008 - 2012
Louisiana	2001 - 2005, 2008	2009 - 2013
Maine	2004 - 2008	2009 - 2013
Maryland	2004 - 2008	2009 - 2013
Massachusetts	2004 - 2008	2009 - 2013
Michigan	2004 - 2009	2009 - 2014
Minnesota	2005 - 2009	2010 - 2014
Mississippi	2006	2009 - 2014
Missouri	2004 - 2009	2009 - 2014

Remeasured annual plots		
State	**Time 1 year range**	**Time 2 year range**
Nebraska	2004 - 2008	2009 - 2013
New Hampshire	2003 - 2008	2009 - 2013
New Jersey	2004 - 2008	2009 - 2013
New York	2003 - 2008	2009 - 2013
North Carolina	2002 - 2007	2003, 2005 - 2007, 2009 - 2014
North Dakota	2004 - 2009	2009 - 2014
Ohio	2003 - 2008	2009 - 2013
Oklahoma (East)	2008	2010 - 2013
Pennsylvania	2004 - 2008	2009 - 2013
Rhode Island	2004 - 2008	2009 - 2013
South Carolina	2002 - 2010	2007 - 2013
South Dakota	2004 - 2009	2009 - 2014
Tennessee	2000 - 2009	2005 - 2012
Texas (East)	2002 - 2008	2005, 2007 - 2012
Vermont	2004 - 2008	2009 - 2013
Virginia	2002 - 2003, 2005 - 2010	2008 - 2013
West Virginia	2004 - 2008	2009 - 2013
Wisconsin	2004 - 2009	2009 - 2014

Table 4.—Inventory data used to develop forest carbon estimates presented in this report by state and time (time 1 and time 2) for states where an insufficient number of annual plots have been remeasured. A single cycle of annual plots was split into two statistically valid samples of the state's forest carbon at the start and end of the annual inventory cycle.

	Split annual cycle plots			Split annual cycle plots	
State	Time 1 year range	Time 2 year range	State	Time 1 year range	Time 2 year yange
Alaska (Coastal)	2004 - 2008	2009 - 2013	New Mexico	1999	2005 - 2013
Arizona	2004 - 2008	2009 - 2013	Oklahoma (West)	2009 - 2010	2011 - 2013
California	2003 - 2007	2008 - 2012	Oregon	2003 - 2007	2008 - 2012
Colorado	2004 - 2008	2009 - 2013	Texas (West)	2004 - 2007	2008 - 2012
Idaho	2004 - 2008	2009 - 2013	Utah	2004 - 2008	2009 - 2013
Montana	2004 - 2008	2009 - 2013	Washington	2003 - 2007	2008 - 2012
Nevada	2004 - 2008	2009 - 2013	Wyoming	2000	2011 - 2013

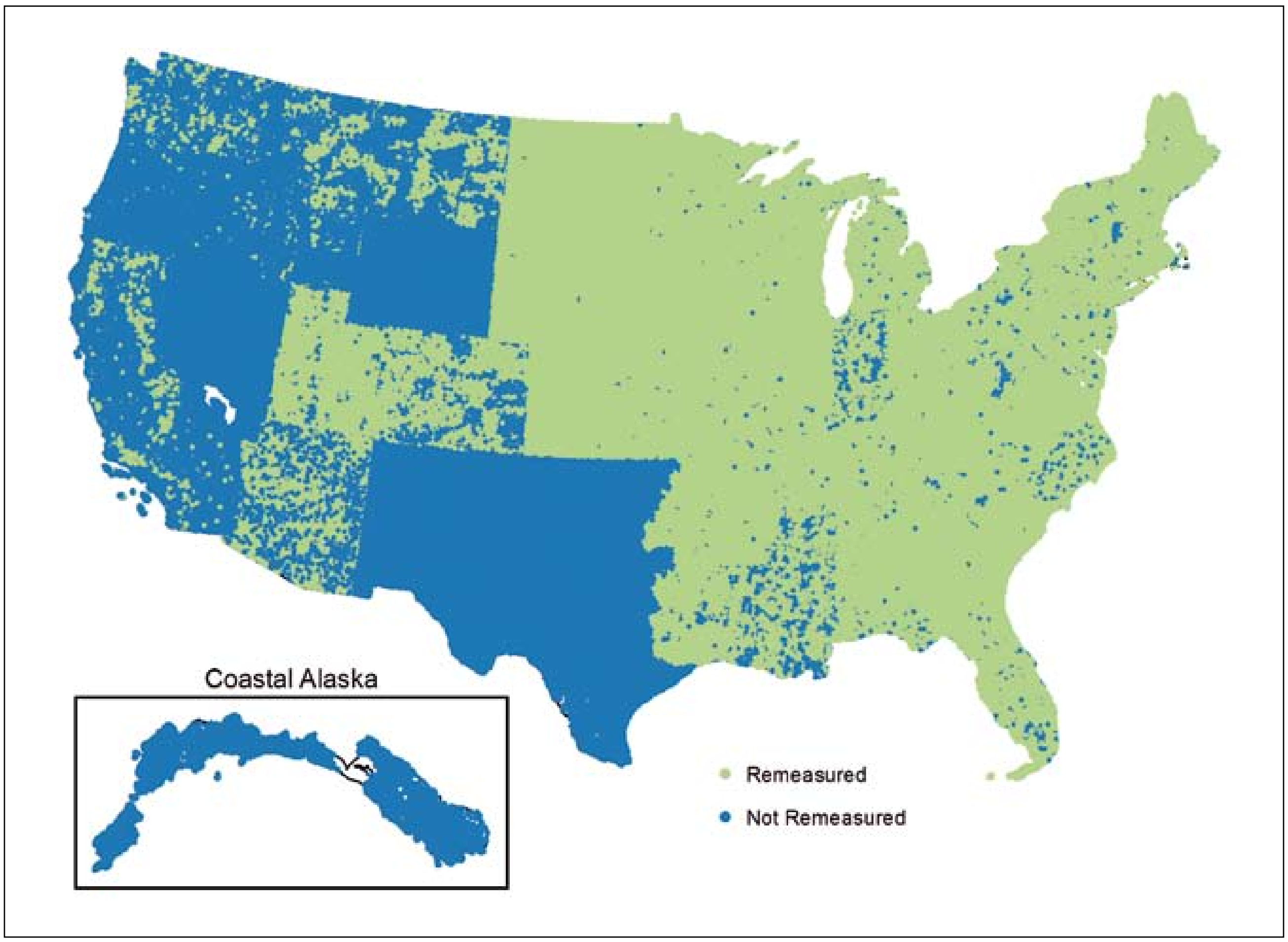


Figure 11.—Annual FIA plots (remeasured and not remeasured) across the United States including coastal Alaska through 2014. Note: Due to the vast number of plots, data points appear spatially contiguous when displayed in small maps. Source: FIA data.

PLANNED IMPROVEMENTS TO THE FOREST CARBON INVENTORY

Uncertainty

Estimates of uncertainty are not provided in this report as techniques for calculating uncertainty are still being developed for application in the United States' official submission to the UNFCCC, which requires such estimates. Good practice guidelines by UNFCCC (IPCC 2006) recognize multiple possible approaches to defining and quantifying uncertainty, and the documentation provides some guidance, particularly for lower tier estimates, but guidelines are not prescriptive. The primary role for uncertainty analysis is in model development and improving estimates by identifying the important sources of uncertainty in a country's report. Overall uncertainty in the current estimate of forest carbon change is a 95 percent confidence interval (USEPA 2015a), which is combined with the emission/sequestration estimates of other sectors. This uncertainty estimate enables comparability across Nations as it is required input to UNFCCC from all signatory Nations.

Uncertainty associated with forest carbon baselines can be substantial compared to other sectors, such as fossil fuel combustion, due to the numerous sources of error that all contribute to forest carbon uncertainty. Sampling error results from using sample plots to estimate the entire forest population (Fig.12a). Estimates of forest carbon stores are also subject to error associated with the models used for calculating carbon (e.g., Melson et al. 2011), with model selection error, parameter estimation error, and residual error (Fig. 12b) being the primary sources. Finally, there is measurement error that arises in the field when collecting measurements such as tree height and diameter (Fig. 12c). Total uncertainty attempts to represent all of these sources of error simultaneously. Monte Carlo approaches have been used to simulate total uncertainty, and this approach for estimating uncertainty associated with the U.S. forest carbon inventory will be evaluated for application in the 2016 submission to the UNFCCC, as Bayesian approaches continue to be researched.

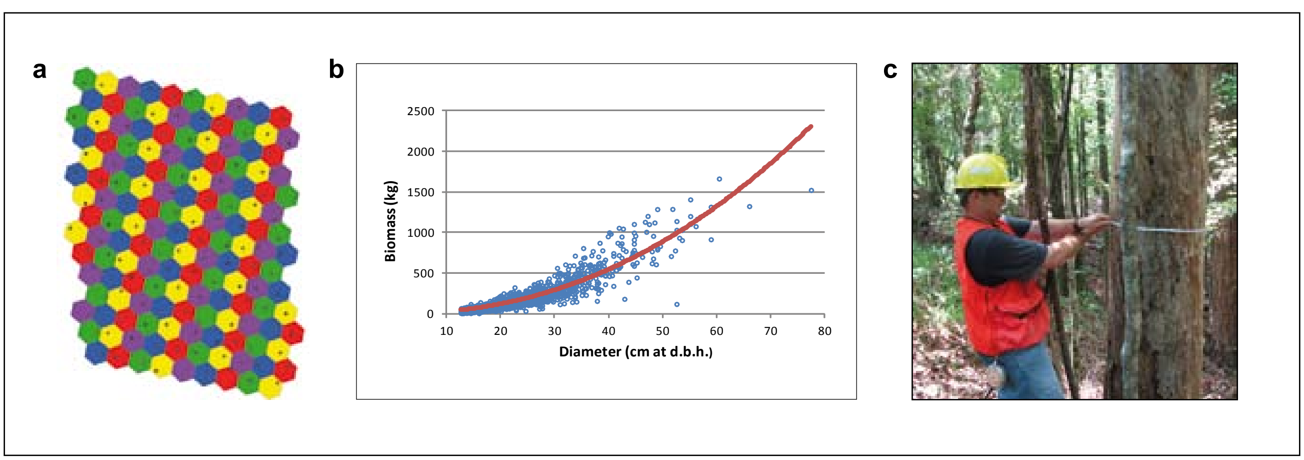


Figure 12.—Sources of forest carbon inventory uncertainty: (a) sampling error, (b) model error, and (c) measurement error. Photo by Kimberly Rowe, U.S. Forest Service.

More Data: Forests, Woodlands, and Urban Trees

The foundation of the forest carbon accounting system is the annual forest inventory. The ongoing annual surveys by FIA are expected to improve the accuracy and precision of forest carbon estimates as new state surveys become available (U.S. Forest Service 2014a), particularly in western states as the annual plot system is remeasured. Hawaii and U.S. territories will be included when appropriate forest carbon data are available (compiled Hawaii data from the annualized sampling design is anticipated in summer 2016) (Fig. 13). In addition, the more intensive sampling of fine woody debris, litter, and SOC on a subset of FIA plots continues and will substantially improve resolution of carbon pools (Westfall et al. 2013). Increased sample intensity of some carbon pools and using annualized sampling data as it becomes available for those states that are not currently reporting on an annual basis are planned for future National Greenhouse Gas Inventories, which will greatly improve the FCAF. Beyond the monitoring of the forest land use, the FIA program is expanding its field measurements to other land uses of woodlands and settlements where tree resources are present. The U.S. Forest Service has been conducting inventories of urban tree carbon (Nowak et al. 2013) for a number of years, with a recent push to begin annual inventories in a number of cities. Carbon inventory-relevant information for these land uses will likely become increasingly available in the future.

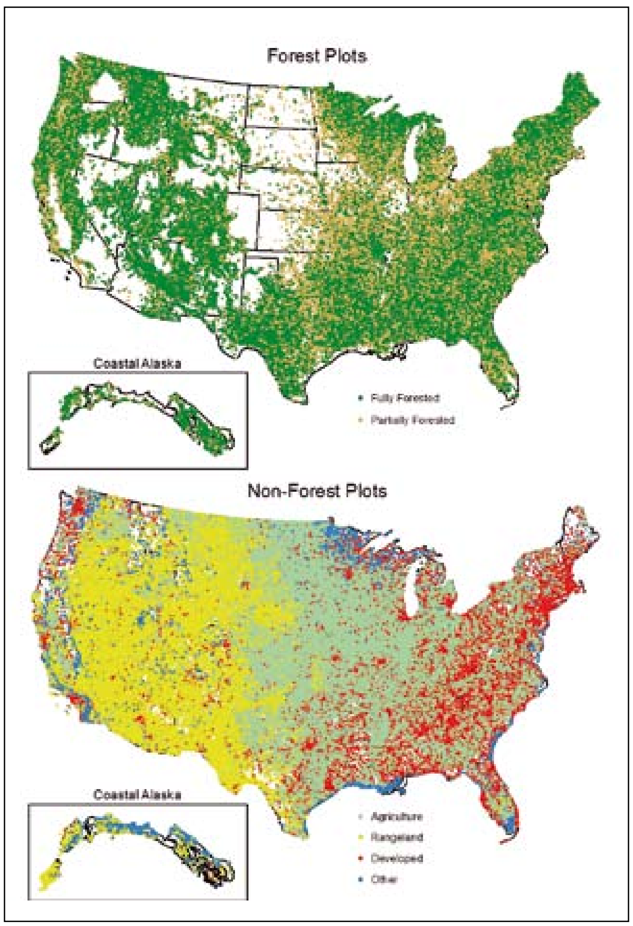


Figure 13.—FIA forest land use plots indicating fully and partially forested plots in contrast to FIA measurement of other land uses across the entire plot network. Note: Due to the vast number of plots, data points appear spatially contiguous when mapped. Source: FIA data.

Refined Land Use Assessment: The Image Change Estimation Program

The 2014 Farm Bill (Agricultural Act 2014; Subtitle D: SEC. 8301 (B) (9)) directs FIA to explore refined approaches to understanding and reporting on changes in land cover and use. In response to this, the FIA program has initiated the Image Change Estimation (ICE) program to interpret imagery from the USDA National Agricultural Imagery Program (NAIP) in a more rigorous manner. The FIA program already employs NAIP imagery to assist with identification of land use (e.g., forest or settlements) across the FIA plot network. However, ICE efforts will identify the land use on every FIA plot concurrent with the measurement cycle of NAIP imagery, which is often far shorter (2 to 3 years) than the typical FIA plot measurement cycle (5 to 10 years). The measurement of land use is not an automated cover interpretation (although a tandem cover assessment will be recorded); rather each FIA plot is manually reviewed by an experienced aerial photogrammetry interpreter. In addition, if change is identified on a plot, the agent of change will be identified if possible (e.g., forest converted to development) (Fig. 14). This program has the potential to greatly refine the monitoring of land use change as a component of the FCAF, as it will operate on the same national plot network.

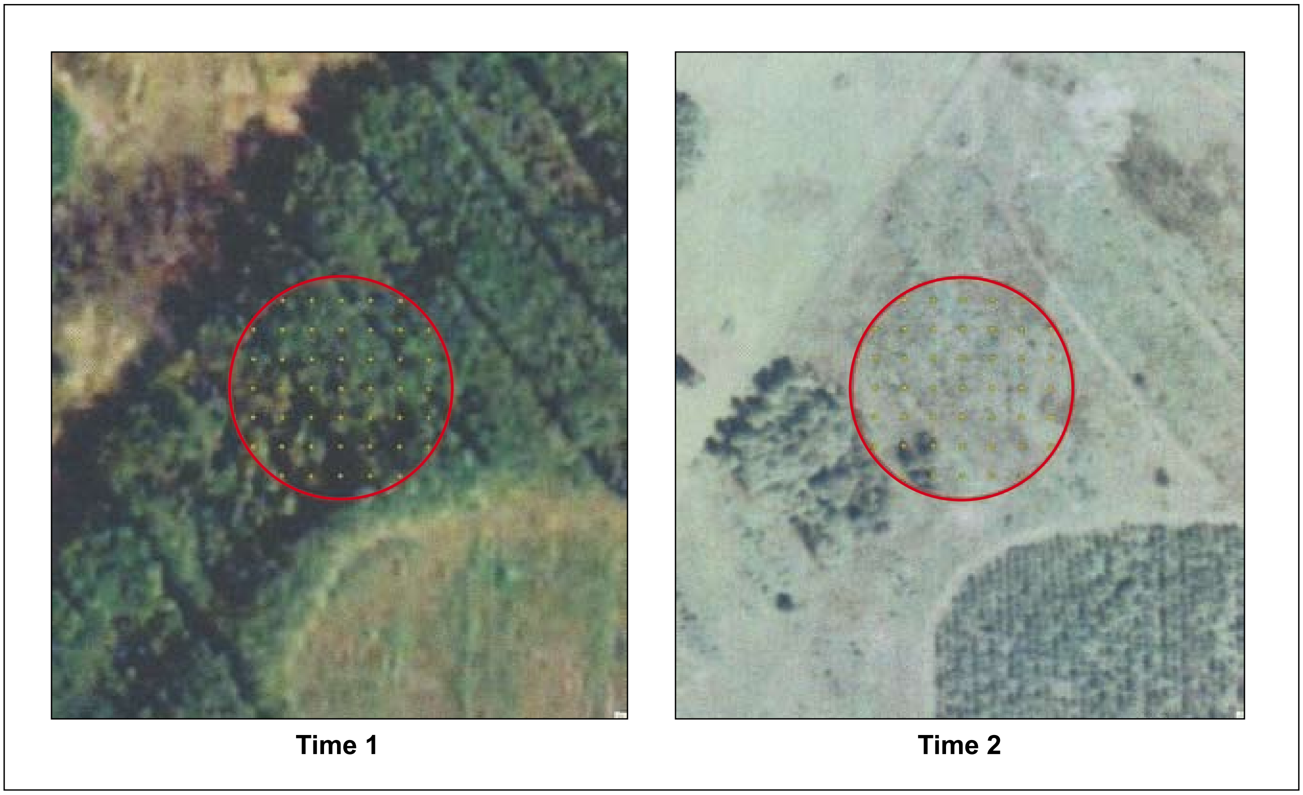


Figure 14.—Measuring land use and land cover changes from time 1 to time 2 on an FIA plot using Image Change Estimation protocols.

Reconciling Improvements to Forest Accounting with All Land Uses

The refinement of forest carbon accounting to benefit U.S. reporting to UNFCCC certainly is not conducted in isolation. Forest land use is part of a larger terrestrial sector entitled “Agriculture, Forestry, and Other Land Uses” (AFOLU), as land use is constantly changing across the United States (Fig. 15). If there is perfect alignment between the carbon accounting of agriculture and forests then the soil carbon associated with a deforested hectare of forest would potentially transfer to a hectare of agriculture, thus balancing out its transfer among land uses. Because land use change can have a substantial effect on the AFOLU carbon accounting, accurately representing the transfer of carbon by pool across the matrix of land use change is paramount. Forests account for the vast majority of terrestrial carbon flux in the United States, and thus it is logical that the refinement of forest carbon accounting should occur first, with subsequent

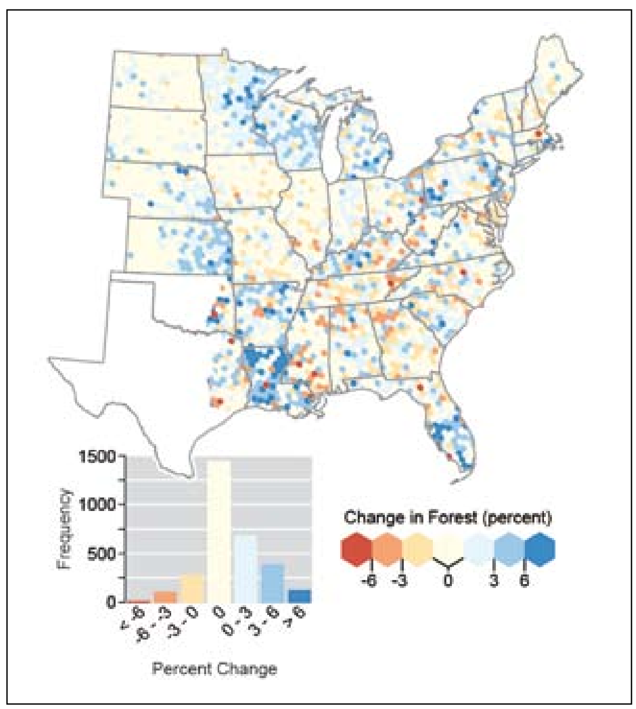


Figure 15.—Percent forest land use change in the eastern United States derived from FIA plot land use identification, 2002-2012 (Woodall et al. 2015).

cascading of carbon accounting improvements across the remaining land uses of AFOLU. It is envisioned that the initiation of a number of improvements, including the implementation of the Image Change Estimation program, refined soil carbon accounting and modeling across all land uses, refined integration between the U.S. Department of Agriculture Forest Inventory and Analysis forest monitoring and Natural Resources Inventory cropland monitoring programs, and expanded monitoring of urban trees and agroforestry systems, will greatly enable refined accounting across the breadth of AFOLU.

Pool Estimation

In an effort to reduce the uncertainty associated with the estimation of individual forest carbon pools, the empirical data and associated models for each pool are being evaluated for potential improvement (Woodall 2012). In the 1990 through 2010 UNFCCC submission, the approach to tree volume/biomass estimation was evaluated and refined (Domke et al. 2012). In the 1990 through 2011 UNFCCC submission, the standing dead tree carbon model was replaced with a nationwide inventory and associated empirical estimation techniques (Domke et al. 2011, Harmon et al. 2011, Woodall et al. 2012). In the 1990 through 2012 Inventory report (2013 NGHGI), the downed dead tree carbon model was refined by incorporation of a national field inventory of downed dead wood (Domke et al. 2013, Woodall et al. 2013). In the current Inventory report (2015 NGHGI), the litter carbon density model was refined with a nearly nationwide field inventory (Domke et al., in review). In this report, a new approach to estimating soil organic carbon is included (Domke et al., in prep.). Components of other pools, such as carbon in belowground biomass (Russell et al. 2015) (Fig. 16), understory vegetation (Russell et al. 2014), and foliage (Clough et al., in review) are being explored for application in future submissions.

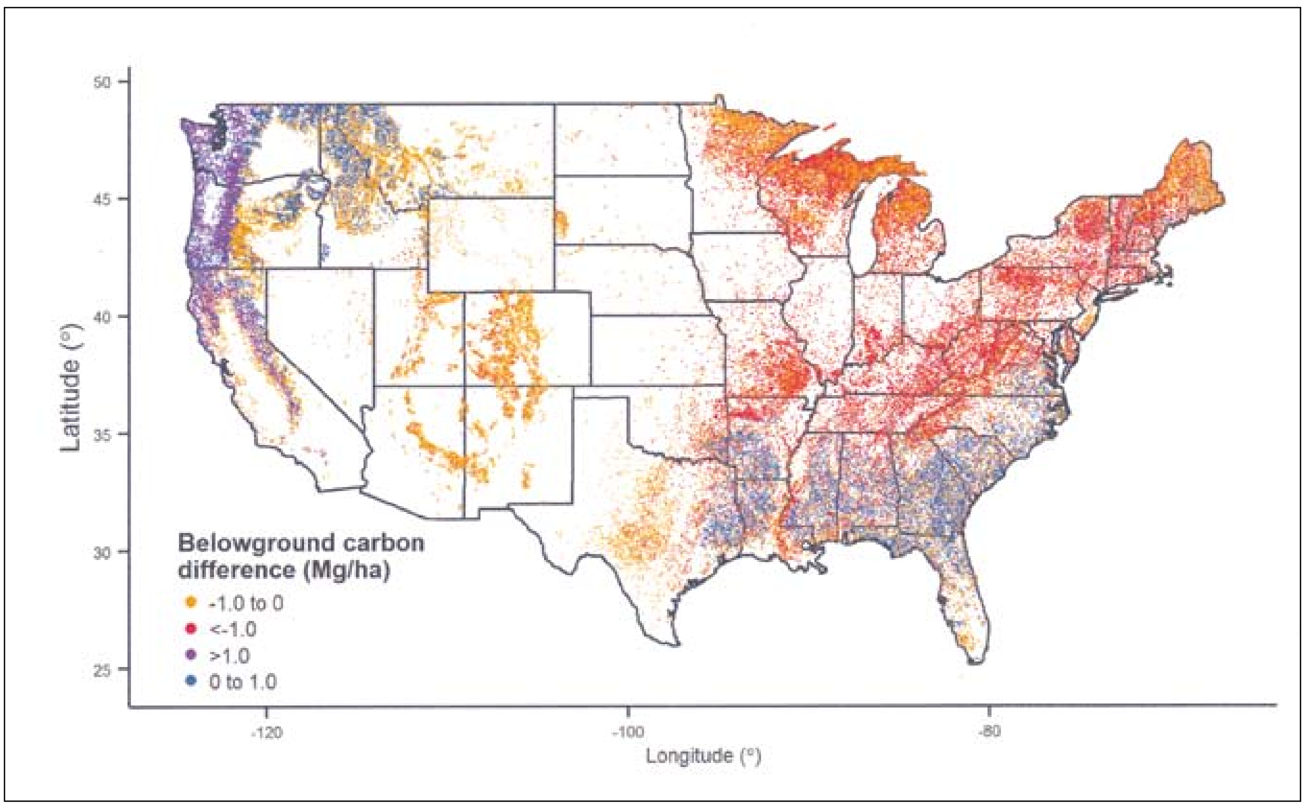


Figure 16.—Distribution of differences between live tree belowground C estimates from the current U.S. National Greenhouse Gas Inventory and refined estimates ($Mg{\cdot}ha^{-1}$). Red colors indicate higher estimated C and purple colors indicate less C (Russell et al. 2015).

The Boreal Forests of Interior Alaska

A national system of field inventory plots is the primary data source for the annual assessment of U.S. forest carbon stocks and stock change to meet reporting requirements under the UNFCCC. The only area of potentially managed forests included under UNFCCC reporting that is not sampled by the national plot network is the boreal forest of interior Alaska (Fig. 17). A preliminary analysis suggests that these forests may represent over a third of all forest carbon in the conterminous United States (Zhu and McGuire, in review), hence the assessment of their carbon balance is critical to the monitoring of the U.S. terrestrial carbon sink. Furthermore, it is the nonlive biomass carbon pools, namely the forest floor, lichen/moss mats, and soils, which may

A vast stretch of boreal forest reaches along the Tanana River in interior Alaska. Photo by Christopher Woodall, U.S. Forest Service.

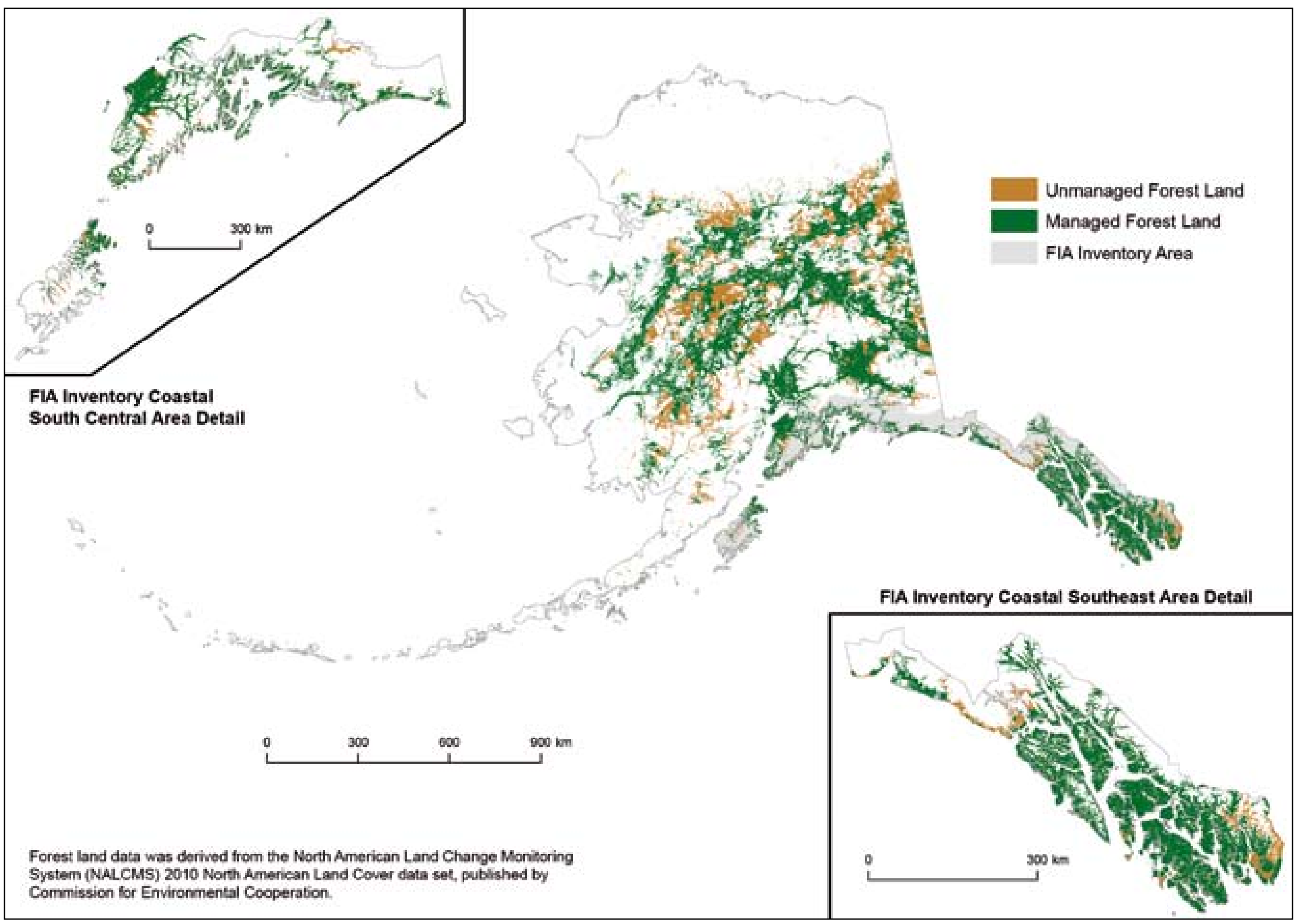


Figure 17.—Delineation of managed and unmanaged forest land in Alaska. Currently south central and southeast coastal Alaska are inventoried by FIA, but interior Alaska remains the only area not sampled by the national plot network.

account for the majority of Alaska's carbon stock that cannot be quantified using remote sensing products alone. A variety of field and research efforts are currently underway to ameliorate these knowledge gaps. In the interim, a managed land analysis has been completed for interior Alaska (Ogle et al., in prep.) which identifies tens of millions of acres of forest that can be considered influenced by humans, and hence deemed managed per UNFCCC good practice guidance.

Disaggregation

The FCAF is designed to monitor carbon to satisfy UNFCCC reporting requirements while monitoring progress towards future commitments. Such a framework aligns well with the FIA inventory as it is intended to address strategic-level questions about forest resources across large geographic areas under a design-based mode of inference (Bechtold and Patterson 2005). Undoubtedly, there is increasing interest in using this information for smaller-scale reporting within the population. The FCAF is also applicable in this case, but the base FIA data may not be sufficiently dense to parameterize the system. By using auxiliary variables from data collected for all population units, such as those obtained from remote sensors, and shifting to a model-based mode of inference, dramatic gains in the precision of estimates can be achieved for disaggregated areas, though possibly at the expense of violating the unbiasedness assumption for the estimators (Gregoire 1998). Through the application of a model-based approach, Wilson et al. (2013) developed spatially extant estimates of forest carbon density for the conterminous United States using FIA and auxiliary data (e.g., multi-temporal satellite imagery from the National Aeronautics and Space Administration [NASA]) (Fig. 18). The relationship between the auxiliary and FIA data was defined using an

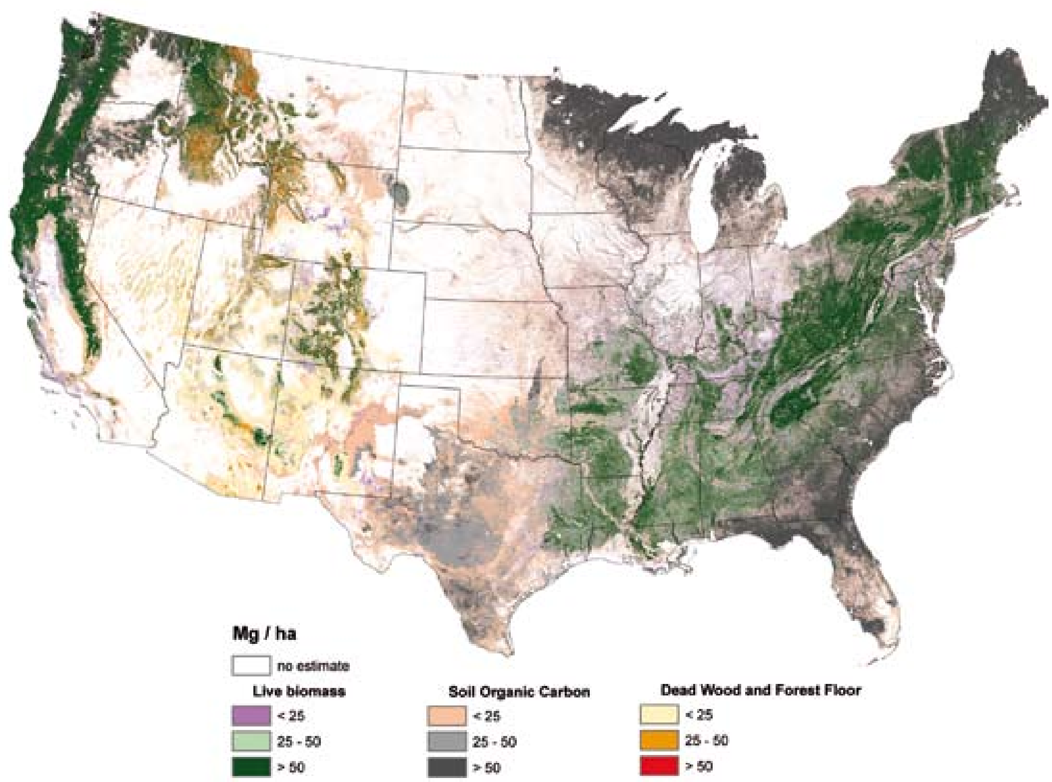


Figure 18.—Forest carbon pool which constitute the plurality of forest carbon at each pixel across the conterminous U.S.: live biomass, soil organic carbon, or detritus (dead wood and forest floor) (Wilson et al. 2013).

ecological ordination model enabled by a k nearest neighbor estimator (Eskelson et al. 2009). It provides an estimate for each unsampled unit in the population as a weighted average of the observed response variable for the k-nearest sample units in the feature space. Research is currently underway to incorporate finer spatial resolution imagery (e.g., Landsat time series) using a similar modeling approach. Although the new accounting framework is designed to meet national scale monitoring needs, it is hoped through research partnerships with stakeholders (e.g., national forests or states) that valid downscaling techniques can be developed to disaggregate national results to the entity level. These finer scale estimates of carbon density and land use may be used to parameterize the FCAF so that smaller areas can be monitored.

Harvested Wood Products

Carbon stored in long-term harvested wood products (HWP) is an important driver of carbon sequestration within the forest sector and as such is included when estimating the contribution of the forest sector to greenhouse gas sources and sinks. For example, in 2013 the accumulation of carbon in HWP was 19.3 Tg·yr $^{-1}$ (USEPA 2015a), which was as large as accumulation rates in litter, standing dead trees, and understory pools combined. However, the HWP estimates through the Woodcarb II model (Skog 2008) are currently exogenous to the FCAF. Efforts to more directly incorporate HWP within FCAF will further increase the analytical capacity to assess carbon dynamics in the United States and provide for consistent scenario-based projections.

The key link between FCAF inventory estimates and HWP estimates is domestic harvest. Domestic harvest simultaneously influences sequestration within the forest and material moving into durable wood products. The attribution of forest carbon dynamics allows for the development of relationships between harvest effects witnessed in the inventory and quantities of wood products observed from a census of mills. These two sources of information exhibit a strong relationship (ordinary linear regression; $R^2 = 0.98$) when observed at an aggregate scale (Fig. 19). Further research is needed to determine the relationship among products, imports, and exports. As these relationships are quantified, the FCAF will also support a HWP module.

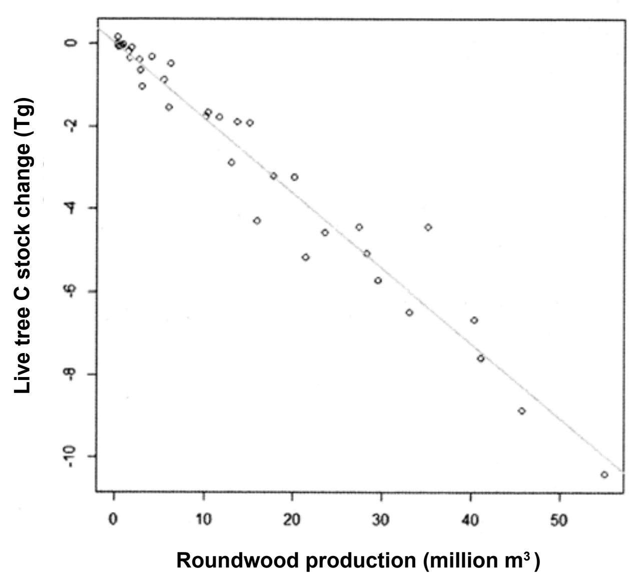


Figure 19.—The relationship between live tree C stock change from cutting in the inventory and of roundwood production (m ^{3}) from wood using facilities. The figure is based on the eastern United States where state-level production is compared to state-level changes in live tree carbon from cutting.

RESEARCH TO IMPROVE AND DISSEMINATE THE FOREST CARBON INVENTORY

National Volume/Biomass Study

National, regional, state and county estimates for both bioenergy and greenhouse gas analyses are derived from FIA field data that rely on individual tree species volume/biomass models. Recently, there has been an increasing need for tree biomass estimates, including various portions of the tree (e.g., merchantable bole and stumps), that requires not only a re-evaluation of older volume/biomass models but perhaps development of new modeling approaches. Unfortunately, there has been no consistent national source of individual tree volume/biomass measurements of all tree components. To ensure FIA estimates provide an accurate representation of forest resources and trends, comprehensive data on tree biomass are needed. These data would provide: (1) a means of assessing current FIA methods, and (2) a basis for nationally-consistent estimation of biomass/carbon. Unfortunately, obtaining such data is both time consuming and expensive, as very detailed measurements on individual trees are required.

To accomplish the considerable amount of work necessary, FIA has engaged a number of partners and stakeholders including: University of Maine, Potlatch Corporation, University of Montana, University of Georgia, Rayonier Inc., U.S. Forest Service Forest Management Service Center, Michigan State University, Oregon State University, National Council for Air and Stream Improvement Inc., Virginia Polytechnic Institute and State University, Weyerhaeuser NR Company, and U.S. Forest Service Forest Products Laboratory. The objective of this study is to collect data (Fig. 20) and develop methods for estimating the biomass/carbon content of individual trees (Weiskittel et al. 2015). Once developed, these methods will have wide-ranging application; however, the primary purpose is for application to trees measured by FIA. These methods will provide a nationally-consistent basis for assessments of current conditions and trends in forest resources. In addition to providing consistent methods and definitions nationwide, substantial increases in analytical flexibility will be realized.

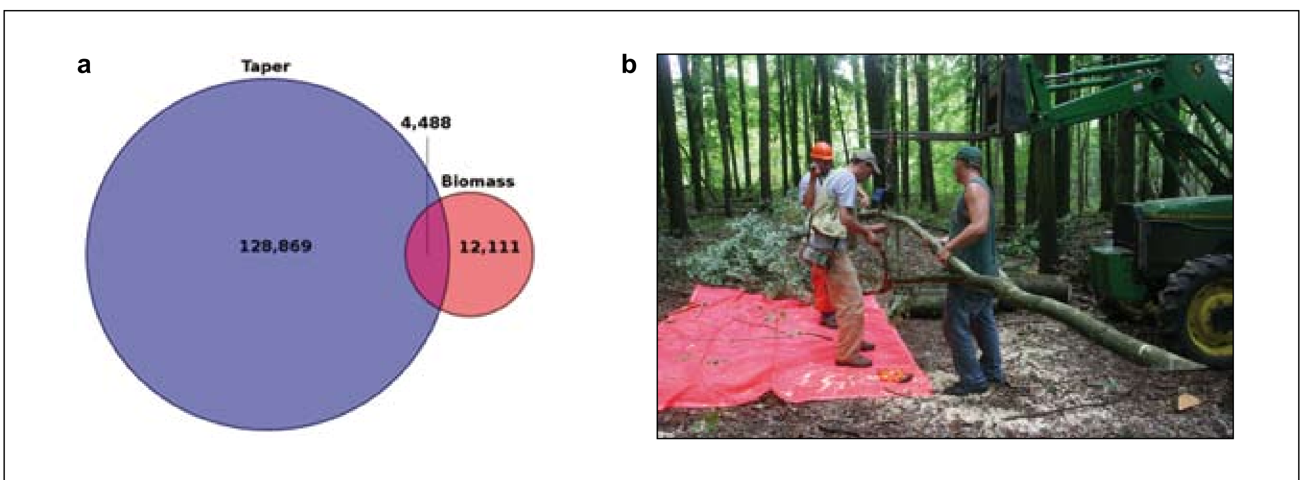


Figure 20.—The national volume study has already gathered thousands of legacy individual tree observations, such as taper and biomass data collected from often overlooked data files spanning nearly a century (a) in addition to contemporary felled tree studies (b) to augment gaps in the legacy dataset. Photo by David MacFarlane, Michigan State University, used with permission.

Remote Sensing of Forest Carbon

Remote sensing combined with field inventory data can provide spatially and temporally consistent biomass estimates. Strong statistical relationships between LiDAR forest structure metrics and field-measured biomass enable accurate spatial predictions of biomass well beyond the plot locations (e.g., Pflugmacher et al. 2014) (Fig. 21). But LiDAR data remain expensive and are limited historically. Landsat data are available everywhere since 1972 and can be linked to the LiDAR biomass estimates to extend those over space and time. A single date of Landsat data does not correlate well with biomass over a wide range of biomass values; however, the strength of the Landsat data is in the time series. Because disturbance and recovery history are strong determinants of current biomass, history metrics (e.g., predisturbance reflectance trend, year of disturbance, causal agent and magnitude of disturbance, and recovery rate) derived from times series data transcend the weakness of the biomass to single-date Landsat relationship. The advantages are twofold: (1) high-quality current biomass maps can be derived for any locations where there are samples of LiDAR data (i.e., LiDAR strips) supported by field measurements; and (2) the annual statistical models can be walked back to an arbitrary date (e.g., 1990) using the history metrics prior to that date, thereby providing an annual time series of biomass maps using a consistent set of methods so that trend lines are devoid of artifacts associated with changes in sample design or approach. The basic methodology has been tested and published. A current NASA-Carbon Monitoring Systems research effort is extending the approach across six diverse forest areas (~22,500 km^2 each) of the conterminous United States.

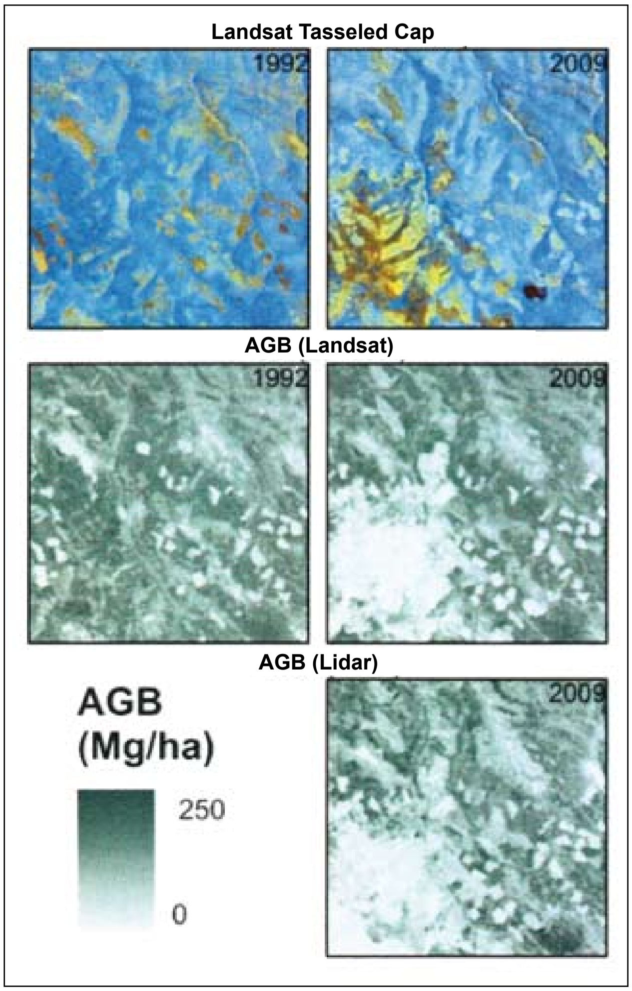


Figure 21.—Example of integrating Landsat and LiDAR information to create robust maps of aboveground live tree biomass that can reduce the lack of temporal sensitivity often associated with delays in remeasuring forest inventory plots following disturbances such as wildfire (Pflugmacher et al. 2014).

Inventorying Boreal Forest Carbon: The Tanana Experiment

The interior Alaska boreal forest biome represents one-fifth of the forest land in the entire United States. Despite the importance of these natural resources to local Alaskan communities, the ecological significance of changes in these resources and their role in the global energy, water, and carbon cycles, interior Alaska is the only forest ecosystem in the country that is not currently being funded for monitoring as part of the national Forest Inventory and Analysis program. A full inventory of interior Alaska could answer fundamental and pressing questions about this important landscape, including:

- What is the status and condition of forests in interior Alaska, and how can they be sustainably managed to provide woody biomass to support bioenergy production in remote communities?

- How are changes in forest composition and condition affecting the quality of wildlife habitat (e.g. caribou) and associated effects on subsistence economies?
- How much carbon is stored below ground in cold, moist soils?
- How vulnerable is this carbon reservoir to potential changes in the wildfire regime, insects, and disease?
- How can the FIA program draw from the local knowledge of natural resources, and in turn provide employment opportunities in these remote areas of the state?

The U.S. Forest Service initiated an inventory pilot in the Tanana Valley of interior Alaska in the summer of 2014 to evaluate a cost-effective inventory design utilizing a reduced sample of field plots and state-of-the-art airborne remote sensing which enables FIA to inventory the entire state at a cost level of $25 million over 10 years—less than one-fifth the cost of the traditional FIA sampling design. Field measurement protocols specific to boreal forest conditions are being examined including: (1) ground cover measurements to quantify biomass/carbon of lichens and mosses; (2) soil core sampling to quantify soil carbon content; (3) using two microplots (or one larger microplot) to increase sampling of small (2.54 to 12.7 cm) diameter trees; and (4) using high-precision global positioning system (GPS) to enable accurate registration of field plots to airborne remote sensing data. The U.S. Forest Service has built partnerships with a number of groups to leverage resources and expertise for this pilot work. NASA's Goddard Space Flight Center augmented the FIA sample with detailed measurements acquired from a newly-developed LiDAR-hyperspectral-thermal airborne remote sensing instrument (G-LiHT) (Cook et al. 2013) that provides detailed measurements of 3-D forest structure (tree heights), species composition, and condition (e.g., insect damage) (Fig. 22). The State of Alaska Division of Forestry (Tanana Valley State Forest) assisted with logistics planning and in-kind support. The University of Alaska, Fairbanks has been instrumental in logistics planning, protocol development, and ground-access field plot data collection. Finally, the U.S. Fish and Wildlife Service aided with protocol development and ground plot location in the Tetlin National Wildlife Refuge.

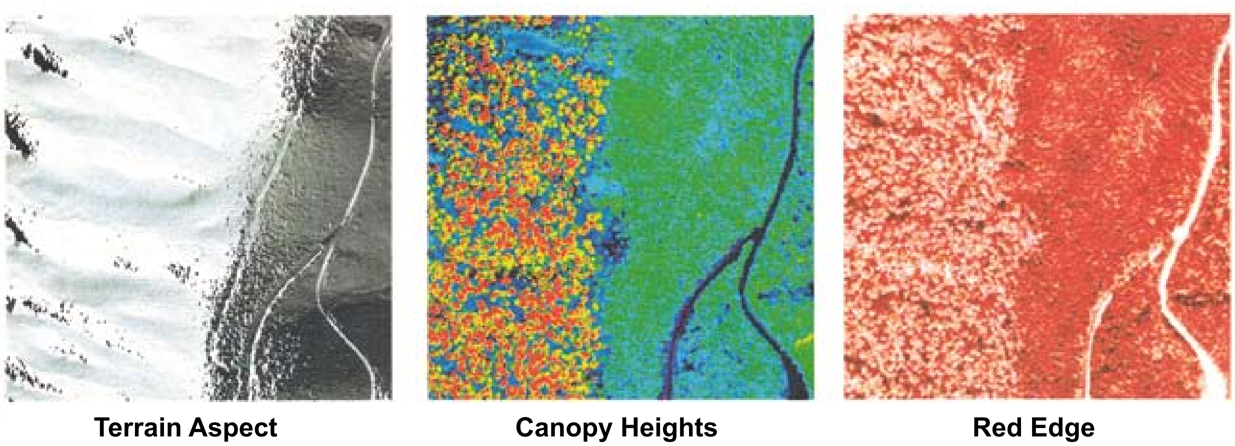


Figure 22.—Spatially explicit estimates of terrain aspect, tree canopy heights, and red edge (i.e., measure of canopy stress) derived from NASA Goddard's G-LiHT and hyperspectral data, 300 m swath, interior Alaska, 2014.

Bayesian Hierarchical Models for Uncertainty

A key challenge of deriving national forest carbon stocks from the FIA database is capturing uncertainty that arises across different scales within the data (i.e., from tree to plot, from plot to Nation). Monte Carlo approaches to estimating total uncertainty provide initial estimates of uncertainty within FCAF (Fig. 10); however, other uncertainty procedures are being researched. For example, we are evaluating a hierarchical modeling framework, based on Bayesian statistical inference, to provide robust uncertainty estimation for national forest carbon stock estimates. This approach presents several key advantages when compared to other methods: (1) uncertainty is determined by observed data hence removing the need to make assumptions; (2) tree and plot scale errors are seamlessly aggregated, allowing for realistic reporting of uncertainty bounds around national forest carbon stocks; (3) the framework is easily expanded and updated as new data is collected; (4) a hierarchical structure integrates with satellite imagery and other remote sensing data which enables high resolution mapping of forest carbon; and (5) this approach accommodates prediction and uncertainty estimation across space and through time (Fig. 23).

Ongoing work is focused on foliage biomass (Clough et al., in review), which is a carbon pool that is difficult to quantify due to tremendous variability (see Pool Estimation section on page 31). Results show markedly higher uncertainty than has been previously reported, with important consequences for reporting stocks at the national level. Future work seeks to expand the framework to other biomass pools and will lead to the development of user-friendly tools to facilitate wider adoption of hierarchical models for quantifying forest carbon stocks and robust quantification of their associated uncertainty throughout the FCAF.

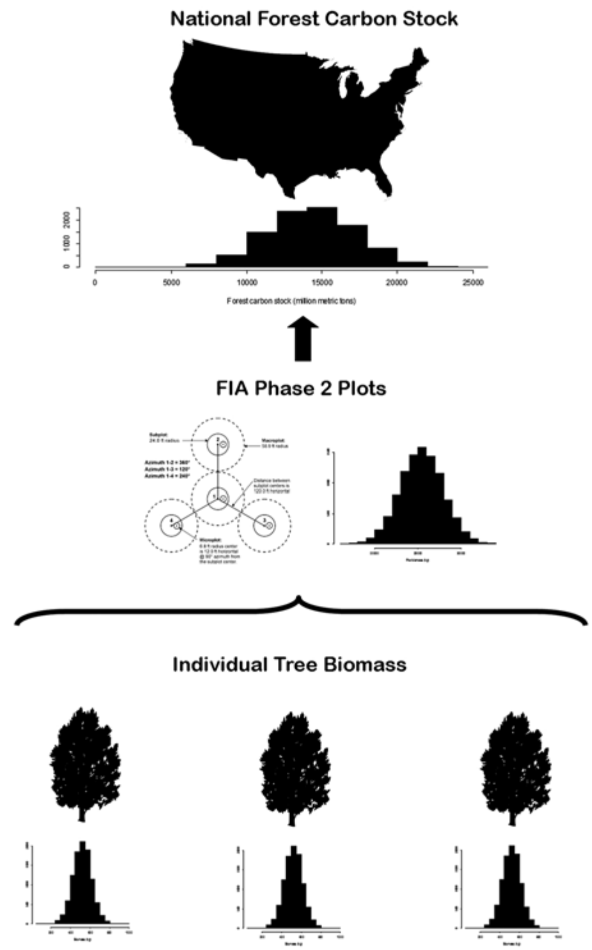


Figure 23.—Bayesian approaches to estimating uncertainty enable the integration of numerous error sources into final estimates of uncertainty.

Surf Forest Carbon with your Thumb: The Forest Carbon Xplorer

The FIA program conducts a systematic inventory of U.S. forests that serves as not only the primary source of national statistics but also supports informed forest management. This wealth of data has been analyzed to provide wall-to-wall spatial geographic information system (GIS) coverage of forest carbon estimates by pool across the lower 48 states to support carbon monitoring. Through a research agreement and collaboration with the University of Minnesota, an online, mobile/web browser map application (app) has been developed that provides a 21st century digital experience of the distribution of the forest carbon estimation in the FIA program (Fig. 24). This web and mobile software tool (forestcarbonx.umn.edu) enables the public to learn about carbon and how much is stored in their vicinity by using the location of the user's phone or tablet. The data is presented interactively on a map along with charts, graphs, and links to related resources. The intended audience is anyone interested in exploring forest carbon information. The tool is a web browser map application for smartphones, tablets, and desktop use that primarily works online but that can also be used offline with simplified functionality. This provides any range of users with access to the carbon summaries in the field and at the desk.

Timely Attribution of Carbon Emissions by Disturbance

Funded under NASA's Carbon Monitoring System program, a team of researchers from Applied GeoSolutions, the Jet Propulsion Laboratory, Winrock International, the U.S. Forest Service, and NASA Ames Research Center has worked together to develop a methodology based on a combination of ground inventory and satellite observations to resolve the drivers of forest carbon emissions and sequestration at 1 ha spatial resolution in the continental United States for 2006 to 2010 (Fig. 25). Using this method, the team found that 75 percent of the carbon emissions committed during this period originated from anthropogenic sources, including harvest (69 percent) and land use change (6 percent). The remaining committed emissions were from natural sources, including fire (10 percent), wind

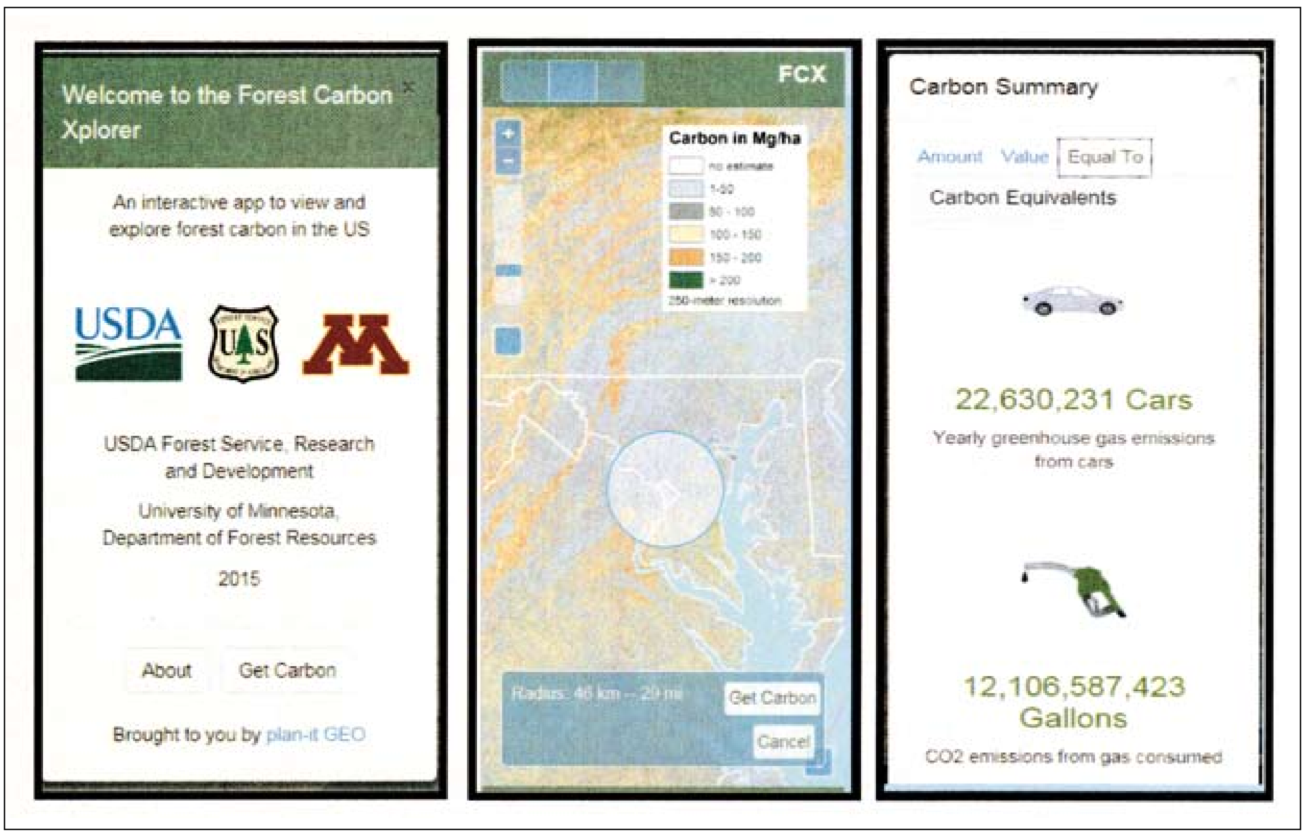


Figure 24.—Example screenshots from Forest Carbon Xplorer (forestcarbonx.umn.edu), a smartphone application that allows users to explore gridded forest carbon data and equivalents using their phone's location.

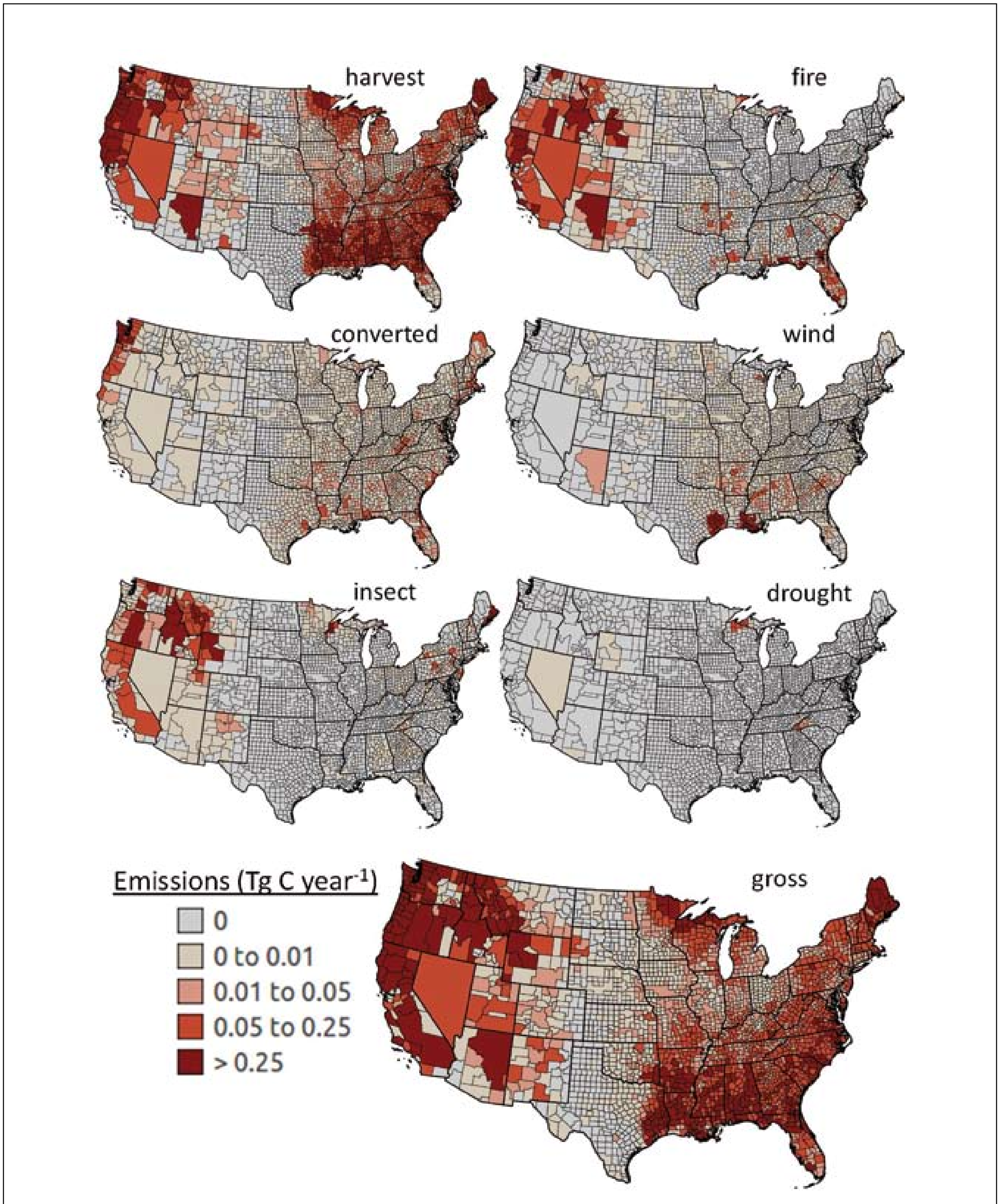


Figure 25.—Average annual committed emissions attributed to the most likely source and estimated at the county scale except where reduced observations necessitated combining counties. Combining these sources of emissions results in estimates of committed gross forest carbon emissions from disturbance occurring between 2006 and 2010.

(7 percent), insect outbreaks (7 percent), and droughts (<1 percent). This was accomplished by integrating the nationally consistent FIA database with a host of products derived from earth observation satellites, including fire from Monitoring Trends In Burn Severity (MTBS) (Eidenshink et. al. 2007), forest cover change (Hansen et. al. 2013), and the National Land Cover Database (NLCD) (Homer et. al. 2015).

The framework and accompanying results from this research represent a step towards enabling the disaggregation of natural and anthropogenic causes of carbon fluxes in forest land of the United States. The results also allow U.S. policy makers and negotiators to better understand the drivers of forest carbon fluxes more completely so that they can participate more effectively in domestic policy discussions about forest management and monitoring as well as in the upcoming international negotiations. For example, the team found that timber harvesting, and not land use change or fire, was the largest source of gross emissions from U.S. forests between 2006 and 2010. Integration of results from this and other studies should further enable development of future U.S. carbon inventories that include disturbance attribution and full land use change accounting in expectation of post-2020 commitment requirements.

CONCLUSIONS

The annual monitoring of forest carbon in the United States is critical to both domestic and international needs for forest managers and policy makers alike as forests annually offset almost 15 percent of carbon dioxide from the combustion of fossil fuels in the United States. In an effort to improve the forest carbon inventory that the United States submits annually to the United Nations Framework Convention on Climate Change, a new accounting framework was introduced that moves the nationally consistent forest inventory backward and forward in time to meet reporting standards back to the 1990 baseline year while enabling forecasting of future forest carbon dynamics (per biennial reporting). Preliminary results from the new Forest Carbon Accounting Framework demonstrate the ability of the new framework to both backcast the annual inventory system while attributing changes in forest carbon to disturbances and delineating land use change from forests remaining forest. Numerous improvements are planned, such as refining the estimation of individual carbon pools and land use change identification, which can be incorporated into the framework with future iterations. The National Greenhouse Gas Inventory will continue to be refined as new data become available and numerous areas of emerging research are identified that someday may substantially improve our ability to monitor forest carbon.

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English Equivalents

When you know:	Multiply by:	To find:
Centimeters (cm)	0.394	Inches
Meters (m)	3.28	Feet
Hectares (ha)	2.47	Acres
Square meters (m^2)	10.76	Square feet
Kilograms (kg)	0.0011	Tons
Kilograms per cubic meter ($kg\ m^{-3}$)	0.0624	Pounds per cubic foot
Megagrams per hectare ($Mg\ ha^{-1}$)	0.446	Tons per acre
Teragram (Tg)	1,102,311	Tons
Square meters per hectare (m^2/ha)	4.37	Square feet per acre

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As a signatory to the United Nations Framework Convention on Climate Change, the United States annually prepares an inventory of carbon that has been emitted and sequestered among sectors (e.g., energy, agriculture, and forests). For many years, the United States developed an inventory of forest carbon by comparing contemporary forest inventories to inventories that were collected using different techniques and definitions from more than 20 years ago. Recognizing the need to improve the U.S. forest carbon inventory budget, the United States is adopting the Forest Carbon Accounting Framework, a new approach that removes this older inventory information from the accounting procedures and enables the delineation of forest carbon accumulation by forest growth, land use change, and natural disturbances such as fire. By using the new accounting approach with consistent inventory information, it was found that net land use change is a substantial contributor to the United States forest carbon sink, with the entire forest sink offsetting approximately 15 percent of annual U.S. carbon dioxide emissions from the burning of fossil fuels. The new framework adheres to accounting guidelines set forth by the Intergovernmental Panel on Climate Change while charting a path forward for the incorporation of emerging research, data, and the needs of stakeholders (e.g., reporting at small scales and boreal forest carbon).

KEY WORDS: forest, carbon accounting, baselines, attribution, United Nations Framework Convention on Climate Change

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