California Forest and Rangeland Greenhouse Gas Inventory Development

FINAL REPORT

California Air Resources Board Agreement 10-778

STATE OF CALIFORNIA AIR RESOURCES BOARD

Submitted December 30, 2013

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ACKNOWLEDGEMENTS

We appreciate the productive discussion and constructive criticism from the interagency technical working group: Chris Keithley and Mark Rosenberg (California Department of Forestry and Fire Protection); David Stoms (California Energy Commission); Mark Wenzel (California Environmental Protection Agency); and Bruce Goines and Carlos Ramirez (USDA Forest Service Region 5). We thank Natalie van Doorn, Sheri Spiegal, Debra Larson, and John Sanders for their research and computational support. Carlos Ramirez and the USFS remote sensing lab provided vital spatial data analysis. Klaus Scott from the California Air Resources Board made significant technical and intellectual contributions throughout this project. We appreciate his help.

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EXECUTIVE SUMMARY

The goal of this project was to improve the Air Resources Board's periodic statewide inventory of atmospheric CO_2 removal and greenhouse gas emissions on forest, range, and other lands in California. To meet the primary requirement of a data-driven process, we used a stock-change assessment to track carbon dynamics. Other operational requirements included: complete state coverage; repeat measurements over time; continuous data gathering in the future; conformity to Intergovernmental Panel on Climate Change guidelines; public availability; moderate to fine spatial resolution for remote sensing data; and minimum data processing needed before analysis. After evaluating several remote sensing options, we decided to use the United States Geological Survey's Landscape Fire and Resource Management Planning Tool (Landfire) as the framework for our efforts. We assigned carbon densities to spatial units defined by vegetation type, vegetation cover, and vegetation height as determined by Landfire. We calculated carbon densities from public data sources including the United States Forest Services' Forest Inventory and Analysis Program, published literature values, and the National Aeronautics and Space Administration's Moderate Resolution Imaging Spectroradiometer. Throughout we made a sustained effort to quantify the uncertainty in our procedures.

We applied our stock-change approach to estimate carbon increases/decreases in the analysis area from 2001 to 2008. Our assessment included all carbon pools except soil. Between 2001 and 2008, the total carbon stored in the forests and rangelands of California decreased from 2,600 million metric tons of carbon (MMTC = 10^6 MgC) to 2,500 MMTC. Aboveground live carbon decreased ~2% and total carbon decreased ~4%. Given our estimate of uncertainty (95%CI = ± 26 MMTC), a stock change of 100 MMTC represents a statistically significant loss of carbon at an annual rate of approximately 14 MMTC y^{-1}. In general terms, 61% of the loss was due to a reduction in the carbon stored per area (i.e., carbon density); the remaining 39% was due to a reduction of the analysis area. Much of the decrease in carbon density was due to wildfire-related transitions of shrublands to grasslands. Much of the decrease in analysis area was due to the conversion of forest and range lands to agriculture.

Our estimate of a carbon decrease on the order of 14 MMTC y^{-1} contradicted expectations. However independent validations and consistency checks with published statewide estimates attest to the robustness of our stock-change methodology. However, we suspect that our reliance on Landfire vegetation layers limits the resolution at which we can detect tree growth, particularly for mature forests where the trees are taller. In general, our method likely underestimates live tree carbon densities for the most carbon dense forest types in California. Sensitivity analyses showed that remote sensing error accounted for more of the overall uncertainty than other factors. Our results provide the first spatial estimates of vegetation carbon changes and uncertainties for the entire state and establish the beginning of a time series to track carbon emissions and sequestration in California ecosystems.

DISCLAIMER

The statements and conclusions in this report are those of the authors from the University of California and not necessarily those of the California Air Resources Board. The mention of commercial products, their source, or their use in connection with material reported herein is not to be construed as actual or implied endorsement of such products.

1. INTRODUCTION

1.1 Background

Greenhouse gas (GHG) emissions from motor vehicles, power plants, deforestation, and other human activities have increased carbon dioxide (CO_2) to its highest concentrations in the atmosphere in 800,000 years (Lüthi et al. 2008). As a result of these emissions, global average surface temperature have increased (mean ± 90% CI) by 0.9 ± 0.3 ºC from 1901 to 2012 (Intergovernmental Panel on Climate Change [IPCC] 2013a). These changes in climate have in turn substantially impacted species and ecosystems in the United States (Grimm et al. 2013) and around the world (IPCC 2007).

In an effort to reduce changes in climate, the State of California in 2006 enacted the Global Warming Solutions Act (Assembly Bill 32, <http://www.arb.ca.gov/cc/ab32/ab32.htm>). The Act requires the California Air Resources Board (ARB) to set statewide GHG emission limits, to develop regulations to reduce emissions, and to regularly inventory GHG emissions to and removals from the atmosphere. As part of this inventory, the ARB must account for GHG exchanges in forest and rangeland ecosystems. Vegetation naturally removes GHG's from the atmosphere, reducing the magnitude of climate change. Globally, vegetation and soils removed carbon from the atmosphere at a rate (mean ± 90% CI) of 2.5 ± 1.3 billion Mg y^{-1} from 2002 to 2011, compared to fossil fuel emissions of 8.3 ± 0.7 billion Mg y^{-1} and deforestation emissions of 0.9 ± 0.8 billion Mg y^{-1} (IPCC 2013a). Recent estimates for California's forest have varied greatly from a net carbon uptake of 15.7 million Mg y^{-1} (Zheng et al. 2011) to net carbon loss of 0.4 million Mg y^{-1} (USFS 2013).

For its forest and rangeland sector GHG inventory, the ARB currently uses an atmospheric flow approach consistent with the gain-loss approach of the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (Aalde et al. 2006) to estimate greenhouse gas emissions and sequestration from forests and other lands, including wood product pools, within California. Specifically, the inventory estimates CO_2 uptake and emissions of CO_2, methane (CH_4), and nitrous oxide (N_2O) by vegetation growth, wild and prescribed fire, post-harvest slash combustion and decomposition, slash combustion from land clearing for conversion/development, and combustion of harvested biomass for heat and power. The inventory also includes emissions from the decay of discarded wood products, including imported wood, in landfills and composting facilities. In accordance with IPCC guidelines, fossil fuel emissions from forestry operations are not included in the forest sector. Fossil fuel emissions are reported in industrial, energy, and transportation sectors. The forest and rangeland sector GHG inventory does not include emissions and sequestration from agricultural and developed (i.e., urban) landscapes.

1.2 Objectives

The goal of this project was to improve ARB's periodic statewide inventory of atmospheric CO_2 removal and GHG emissions on forest, range, and other lands. The current forest and rangeland GHG inventory is based on a California Energy Commission (CEC) research effort (Brown et al. 2004). This effort used forest inventory data and changes in land use and land cover between 1994 and 2000 to make initial statewide estimates of CO_2 uptake and GHG emissions for forest, range, and other lands. While Brown et al. (2004) did provide valuable insights and identify the challenges associated with GHG quantification, the development of a process for sustained GHG inventory generation and improvement was beyond its scope. Together with methodological, geospatial and temporal data limitations, lack of a process for on-going inventory generation and update has resulted in landscape CO_2 uptake and GHG emission estimates which are extrapolated in both time and space, and have limited basis in actual attributes or processes occurring on the land.

To achieve this goal, we conducted applied research with four objectives:

(1) To develop a data-driven method to quantify stocks and changes of carbon for all land in the State of California, except for agricultural and urban areas, for specific years from approximately 2001 to 2010. Ideally this stock-change approach should conform to international standards developed by the IPCC for GHG inventories (IPCC 2006, 2013b) to ensure consistent reporting under the U.N. Framework Convention on Climate Change.

(2) To quantify GHG emissions and removals due to vegetation cover change, growth and wildfire for the entire analysis area between 2001 and 2008, demonstrating the efficacy of the stock-change method.

(3) To develop an operational method consistent with the atmospheric flow approach currently used by ARB and informed by the stock-change assessment (Objective 1) so that ARB can repeat estimates of vegetation carbon and GHG emissions and removals in the future.

(4) To review specific elements of the quantification process, identified by ARB staff and stakeholders as part of the technology transfer agreement, as priorities for improvement:

4a. Evaluate fuel model loading assumptions used in a wildland fire emission model and recommend possible improvements based on empirical assessments of fuel consumption.

4b. Estimate annual production and discard of California-origin wood products.

4c. Estimate GHG emissions from combustion and decomposition of forest harvest slash.

4d. Estimate GHG emissions from off-site combustion of forest harvest residues and non-agricultural biomass utilized for heat and power.

As a complement to this effort, we are also designing methods, through a companion project for the California Energy Commission, to account for reduced CO_2 uptake in forest areas affected by increases in the number of standing dead trees caused by combination of chronic air pollution, exotic diseases, and insect outbreaks.

1.3 Report organization

The body of this report describes the development (Objective 1) and application (Objective 2) of a stock-change method for estimating carbon uptake and loss from California's forest and range lands. Results from this applied research provide the core input needed to design an operational method (Objective 3). Deliverables from Objective 3 will include the scripting codes, databases, and documented processing steps that together function as a process, such that ARB can update the forest sector GHG inventory as needed. Products from the specific tasks associated with Objective 4 are incorporated in the operational method; descriptions of the data and analysis of these tasks are included as stand-alone appendices to this report.

2. METHODS

2.1 Background

Accurately mapping carbon stocks over large land areas is an essential feature of a stock-change assessment (Goetz et al. 2009). A well-established approach estimates carbon stocks as the product of surface areas of land cover types, stratified by satellite remote sensing, and the carbon densities, derived from field measurements of trees and allometric equations, summed over all land cover types (Achard et al. 2004, DeFries et al. 2007, Harris et al. 2012). The number of land cover types that satellites with moderate spectral or spatial resolutions can accurately discriminate is typically limited to between five and twenty classes (Bartholomé and Belward 2005, Loveland et al. 2000). By relying on such coarse cover classes, carbon densities within a class can vary greatly. This variation can reduce the overall reliability of the map (Goetz et al. 2009).

An alternative to this “stratify–and-multiply” approach (sensu Goetz et al. 2009) is a more direct remote sensing method. For example, Light Detection and Ranging (LiDAR) or high-resolution satellites such as QuickBird, Ikonos, or WorldView can sense physical dimensions of trees to which aboveground biomass directly correlates (Gonzalez et al. 2010, Saatchi et al. 2011, Chen et al. 2012). With these systems, forest carbon content equals the product of the area and the carbon density of each pixel, where carbon density is calculated by applying allometric equations to field measurements of individual trees and correlated to canopy height metrics estimated by LiDAR or tree crown diameter estimated by high-resolution satellite data. This method generates raster coverage of the spatial distribution of forest carbon density with continuous values, thereby avoiding the need to stratify the landscape into classes. However the acquisition and processing of these remote sensing products at the relevant spatial scales can be prohibitively expensive.

The best choice of method depends on the needs of specific measurement and monitoring efforts (Goetz et al. 2009). For the California forest and rangeland GHG inventory, the operational requirements included:

- Complete state coverage;
- Repeat measurements over time;
- Continuous data gathering in the future;
- Conformity to IPCC (2006, 2013b) guidelines;
- Public availability;
- Moderate to fine spatial resolution for remote sensing data;
- Minimum data processing needed before analysis.

Our analysis proceeded through three steps: (1) evaluate remote sensing options in order to select the approach that meets the project’s operational requirements, (2) calculate carbon densities from field inventories necessary to inform remote sensing results, and (3) estimate carbon stocks and stock changes. Given the potential errors and variation of remote sensing data, allometric biomass equations, and other components of forest carbon estimation, we made a sustained effort to quantify the uncertainty in our procedures. At each step, we assessed different data sources and methods for the requirements of an operational GHG inventory system. The area of analysis is the entire area of the State of California, except for agricultural and urban land.

2.2 Remote sensing of vegetation

We first assessed the possibility of using LiDAR or high-resolution satellite data. LiDAR sensors on airplanes can provide metrics of ground and canopy elevation for the calculation of canopy height metrics (Lefsky et al. 2002). Research has demonstrated the use of airborne LiDAR for quantifying carbon in high biomass forests in California (Gonzalez et al. 2010). The expense of acquiring airborne LiDAR data for extensive areas, however, makes the option impractical for the ARB inventory. Other research (Baccini et al. 2008, Lefsky 2010) has demonstrated the use of LiDAR data from the ICESat satellite. ICESat Geoscience Laser Altimeter System (GLAS) global altimetry data (Abshire et al. 2005) is available for selected periods from 2003 to 2009 at 170 m spatial resolution. It is theoretically possible to take the difference between canopy elevation from GLAS and ground elevation from the United States Geological Survey (USGS) National Elevation Dataset (Gesch et al. 2002) at 30 m spatial resolution to calculate canopy height. ICESat only made 16 passes over California, however, and covered only a fraction of the area of the state. We would have needed more passes and passes for multiple years. So, GLAS provided insufficient data for this work. Furthermore, GLAS would have required processing and calibration to field-measured canopy heights.

High-resolution satellite data from QuickBird, Ikonos, or WorldView is not freely available and, indeed, is too expensive for statewide coverage. High-resolution data would also have required processing and calibration to field-measured tree crown diameters. So, we also eliminated that option.

Given the drawbacks of these direct remote sensing methods, we explored different data sources for a land cover approach. Land cover classification must use identical methods over time and data from different years must be co-registered geographically (each pixel lines up over time) to permit determination of land cover change over time. Possible land cover remote sensing options include:

- National Aeronautics and Space Administration (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type (MCD12Q1, Friedl et al. 2010): annual 2001-2007 (available) and 2008-2010 (planned), 250 m spatial resolution, 17 land cover classes;

- USGS National Land Cover Database (NLCD, Homer et al. 2007): 2001 and 2006 (available) and 2011 (in progress, but not yet available), 30 m spatial resolution, 29 land cover classes;

- USGS Landfire (Landscape Fire and Resource Management Planning Tools Project, Ryan and Opperman 2013): 2001, 2008, 2010 (available), 2012 (planned), 30 m spatial resolution, derived from Landsat satellite data, 163 vegetation type classes in California.

Within a land cover class, it is necessary to use another variable to discriminate different levels of carbon density within a single year and growth or mortality over different years. Normalized Difference Vegetation Index (NDVI), an index related to green foliar area (Tucker 1979) and biomass (Tucker et al. 1985), and net primary productivity (NPP), a measure of annual vegetation production, are possible variables. NDVI would need calibration to field-measured biomass. Possible vegetation level remote sensing options include:

- NASA MODIS NDVI (MOD13Q1): every 16 days from 2001 to present, 250 m spatial resolution;

- USGS web-enabled Landsat data (WELD) NDVI (Roy et al. 2010): annual 2006-2010 (available) and 2011-2012 (planned), 30 m spatial resolution;

- NASA MODIS NPP (MOD17A2, Running et al. 2004), every 8 days from 2000 to present, 1 km spatial resolution, vegetation production rate (kg m^{-2} y^{-1}) calibrated to field measured biomass (Turner et al. 2006);

- USGS Landfire vegetation height and cover (Ryan and Opperman 2013): 2001, 2008, 2010 (available), 2012 (planned), 30 m spatial resolution, derived from Landsat satellite data, 39 height classes and 54 vegetation cover classes in California.

After acquiring and testing different sets of land cover and vegetation level remote sensing, the advantages of Landfire data became clear. Landfire combines data from several sources to produce fine-grained spatial units (Rollins 2009) over which field data can be applied. As noted by Goetz et al. 2009, this approach improves the stratify-and-multiply method by providing finer spatial resolution. In addition, the different spatial data layers can be adjusted based on what is known from the field data. When there is detailed field data (e.g., forests), carbon density assignments can be precisely resolved. When data is sparse (e.g., shrublands), generic assignments are more appropriate. As we describe below, this matching allows us to meet a core objective, namely to build a data-driven method. Landfire also meets other project criteria. The USGS has completely processed and calibrated the data against field measurements, posted the data publicly, and provided three different years with plans for future releases. Moreover, the Landfire variables are developed together, providing an internally consistent treatment of land cover and vegetation characteristics.

We downloaded Landfire data from USGS <http://landfire.cr.usgs.gov>. For California <National

Atlas State Boundaries ID 43>, we downloaded the following variables: <us_105 Existing Vegetation Type>, <us_105 Existing Vegetation Height>, and <us_105 Existing Vegetation Cover> for 2001; <us_110 Existing Vegetation Type>, <us_110 Existing Vegetation Height>, and <us_110 Existing Vegetation Cover> for 2008. We used the native Landfire projection (Albers Conical Equal Area US), horizontal datum (North America 1983), and spatial resolution (30 m). USGS divided the state into eastern and western halves, which we combined into a mosaic with a final extent of 41.99767 to 32.536 N latitude, 119.2582 to 124.39264 W longitude. We defined the analysis area by building a mask of all land pixels, except agriculture and urban pixels, within the state boundary given in the 2012 U.S. Bureau of the Census geographic information systems (GIS) file <http://www.census.gov/geo/maps-data/data/tiger-line.html>.

2.3 Calculation of carbon densities

2.3.1 Landfire vegetation classification system <http://www.landfire.gov/vegetation.php>

Landfire assigns an existing vegetation type (EVT) to each pixel that represents the species composition currently at the site. In natural ecosystems, EVT represents plant community types that tend to co-occur in environments with similar biophysical characteristics. In human dominated ecosystems (e.g., farms, cities), EVT represents the primary management inputs. Mapping follows the ecological systems classification framework designed by NatureServe (Comer et al. 2003) – a nationally consistent set of mid-scale (e.g., 10-1000 ha in area) plant associations. EVT's are hierarchical grouped into increasingly coarse units – subclass, class, order – that are consistent with the National Vegetation Classification System (NVCS, Jennings et al. 2009). The five orders used by Landfire are defined by the lifeform of the dominant vegetation, namely tree (38% of the analysis area based in 2008), shrub (35%), herb (15%), no dominant vegetation (5%), and non-vegetated (6%). We examined each Landfire vegetation type and recorded the IPCC (2006) land category to which it belonged: forest (includes both tree and shrub dominated lands), wetland, grassland, other land (natural ecosystems), cropland, and settlements.

In addition to type, Landfire assigns each pixel an existing vegetation cover (EVC) and existing vegetation height (EVH). EVC is the vertically projected percent cover of the live canopy layer for a pixel; EVH is the average height of the dominant vegetation. Both EVC and EVH are expressed as ordinal values. Together these three Landfire products provide sufficient information to define relatively fine-scale biomass classes.

Given the capacity of Landfire, we developed a carbon stock mapping method that retains the simplicity of "stratify and multiply" but mitigates its biggest drawback, namely the ambiguity of within-in class carbon density. By combining vegetation type, cover, and height classes, there are 100's of potential strata. The nature and number of these strata can greatly reduce within-class variation in carbon density. However the challenge associated with so many classes is the availability of sufficient data to "fill" them with estimates of carbon density. For California, the availability of data varies by vegetation type. Therefore we developed type-specific approaches to calculate carbon density. We describe our methods in detail below. See Supplemental Table S1 for a summary.

2.3.2 Calculating carbon density for tree-dominated landscapes.

We relied exclusively on data from the US Forest Service (USFS) Forest Inventory and Analysis (FIA) program to calculate carbon density for biomass classes defined by Landfire as tree-dominated. The FIA program is a statistically sound, national inventory of forest resources that includes a network of field plots distributed at a density of approximately one plot per 2,492 ha. Measurements in these plots (Phase 2) include nested sampling of trees (e.g., species identification, dbh, status, height, and canopy position). In the western United States, FIA plots are measured on a ten-year cycle. The fraction measured in any individual year is designed to be a representative sample of all plots in the region (Bechtold and Patterson 2005). Details of the inventory and access to the data are available online <http://fia.fs.fed.us/>.

We downloaded the FIA 2011 database for California (FIADB Version 5.1, created November 23, 2011). This database included results from plots measured between 2001 and 2009. Exact coordinates of the location of FIA plots are not publically available. To ensure the accuracy of our biomass densities, the remote sensing lab of the USFS Region 5 provided us 2001 and 2008 Landfire vegetation classifications (type, subclass, class, and order), cover class and canopy height of each FIA plot in California using the exact geographic coordinates. They did not release coordinates to us, only the Landfire values for the exact plot locations.

The FIA program provides plot-level estimates of key forest attributes, including those required to meet national requirements for GHG reporting (EPA 2013). Forest carbon is divided into the following pools: live tree (aboveground and total), standing dead tree, live understory vegetation, coarse woody debris, litter, and soil. In many respects the live tree pool is the primary driver as well as the best indicator of carbon storage in forests (Fahey et al. 2010). Moreover, it is the feature that is sensed by the satellites (i.e., canopy cover and height), measured in the field (i.e., tree diameter and height), and predicted by empirical relationships (i.e., allometric volume equations and wood density). Therefore the live tree pool, particularly the aboveground component of live trees, was the key determinant in our inventory.

Recently FIA implemented a nationally-consistent method to calculate tree biomass from inventory measurement referred to as the component ratio method (Woudenberg et al. 2011). However to ensure consistency with existing forest carbon protocols used in California, we retained the regional approach to calculating tree biomass. In the Pacific Northwest (including California), volume and biomass models were developed for the major tree species (Zhou and Hemstrom 2009). Most of these models were based on published papers that predicted wood volume as function of diameter or of diameter and height. The FIA program in the Pacific Northwest Research Station uses separate sets of equations for bole, branch, and bark biomass. Tree bole biomass is scaled directly from volume estimates via species-specific wood density factors. In a comparison, Zhou and Hemstrom (2009) detected only minor differences (3%) in the estimates obtained with the two methods for trees in Oregon.

We developed transfer functions for predicting aboveground live tree biomass (AG) for tree-dominated landscapes from the 3,623 FIA plots that were classified as tree-dominated by Landfire in 2008. These functions were necessary to "fill" all the potential biomass classes despite the large FIA database. Even for the common forests (82% of the tree-dominated landscape), 20% of the possible cover (9) by height (5) classes had no data. To build these functions, we explored the correlation of vegetation type, canopy cover, and height to AG. Based on an analysis of variance, individually all three were significant predictors ($p< 0.01$). We next evaluated the nature of the relationship by comparing the performance of linear, saturating, and power functions. Overall, linear combinations of height and cover proved to be the best approach. They significantly outperformed power functions based on model fits. Saturating functions were difficult to estimate given ordinal cover and height information.

Considering the ecological and statistical relevance of vegetation type, we developed individual transfer functions for each of the 17 most common tree-dominated vegetation types (Table S2). "Common" types were defined as contributing more than 0.5% of the area and having more than 30 FIA plots in the dataset. We fit linear regressions of the general form:

$$\sqrt{AG_{EVT}} = a + bEVC + cEVH + E \qquad \text{(Equation 1)}$$

where AG_{EVT} is the plot-level biomass ("oven-dry") density in Mg ha^{-1}, a is the intercept term; EVC is the upper limit of the Landfire tree cover class (e.g., cover class ≥10% and < 20% was assigned a value of 20); EVH is the upper limit of the Landfire tree height class; b and c are coefficients of EVC and EVH; and E is the standard deviation of the regression. AG_{EVT} was square-root transformed to correct for positive skew in biomass distribution. Positive skew is a common feature of biological data that is routinely corrected using a square-root transformation (Sokal and Rohlf 1995). The error term was calculated based on recommendations in Yanai et al. (2010, Equation 4) and expressed as a relative error of the regression estimate (sensu Whittaker et al. 1974).

We compared reduced versions of the full linear model using the Akaike's Information Criteria (AIC). In total six models were evaluated: EVC only with an intercept term; EVC only without an intercept term; EVH only with an intercept term; EVH only without an intercept term; EVC and EVH with an intercept term (the full model, Eq.1); and EVC and EVH without an intercept term. AIC difference values (ΔAIC), the difference between the AIC value of a given model (AIC_i) and the AIC value of the best approximating model (AIC_{min}), were used to measure the strength of evidence for each model (Burnham and Anderson 2002). Although the interpretation of ΔAIC's is subjective, they provide an intuitive assessment of the strength of support for one model relative to another (Burnham and Anderson 2002). Statistical analyses were conducted in R (3.0.2).

To provide carbon density estimates for the less common forest types with limited plot data ($n < 30$), we developed equations that predict $AG_{SUBCLASS}$ as a function of EVC and EVH for the eight Landfire subclasses defined for tree-dominated landscapes (Table S2). Since Landfire uses a strictly hierarchical classification scheme every EVT is assigned to a subclass. Thus in absence of finer scale information, an EVT "inherits" the prediction for its subclass. For the five tree subclasses with more than 30 samples, we applied the same analytical approach described above. The three remaining subclasses account for a tiny fraction (0.06%) of the forest area. We assigned a mean AG value with a simple standard error for these rare classes (i.e., no stratification with cover or height).

2.3.3 Estimating the uncertainty in the carbon density estimates for tree-dominated landscapes.

The primary sources of uncertainty in our carbon density estimates (sensu Harmon et al. 2007) include: 1) errors in the field measurements of tree; 2) errors in the volume and wood density functions used to calculate tree biomass from field measurements, and 3) errors in the transfer functions that we developed to assign carbon densities to Landfire biomass classes (described above). The FIA program employs a high-quality, statistically robust forest resource inventory with established accuracy standards (Woudenberg et al. 2011, Bechtold and Patterson 2005). For example, Phillips et al. (2000) report negligible contributions from measurement error to FIA-based estimates of forest carbon budgets. In regard to tree biomass, the FIA regional approach in California employs a complex "roadmap" of calculations (Melson et al. 2011). While these roadmaps do provide consistent estimates of the central tendencies (Melson et al. 2011), quantifying the errors involved in all the steps and pieces is a daunting challenge beyond the scope of this effort. Therefore we developed a first approximation of the uncertainty associated with the plot-level estimates of tree biomass reported in the FIA database.

Our approximation was based on the correlation between uncertainty in the plot-level aboveground live tree biomass (expressed as the standard error of the mean) and the mean biomass. We assembled data from published research efforts that included a formal error analysis (Harmon et al. 2007, Battles et al. 2007, Gonzales et al. 2010, Fahey et al. 2010). The dataset (n = 302, Figure 1) represents a diversity of forests and included plots from several of the most abundant forest types in California such as the mixed conifer forest, red fir forest, coastal redwood forest (both old-growth and managed), and the blue oak woodlands. Biomass densities ranged from 7 Mg ha^{-1} to 1,315 Mg ha^{-1}. We used likelihood-based methods (Buckland et al. 1997) to quantify the strength of evidence for alternative models of the relationship between the mean and standard error in plot-level biomass estimates. We considered 11 candidate models in three general functional forms: linear, power, and saturating; we also evaluated models with variation that increase as function of biomass. Based on AIC criteria (Burnham and Anderson 2002), the best model was a linear equation with variation increasing as function of the mean plot biomass (ΔAIC = 11 compared to the next best model; R^2 = 0.49).

We applied Monte Carlo randomizations to propagate and combine the errors that contribute to the uncertainty associated with our measurements of tree biomass (sensu Yanai et al. 2012). From our first approximation model, we generated a standard error for Landfire biomass class estimates. Note that this standard error accounts for field measurements and tree-level biomass calculations (error sources 1 and 2 described above). For the transfer functions (source 3), we used the error of the regression (E from Eq. 1) to quantify the uncertainty (Yanai et al 2010). We then performed 100 simulations with a random draw of the biomass per class followed by a regression assignment that varies based on the error of the regression. We reported the total uncertainty in the biomass class assignments (AG_{EVT} or $AG_{SUBCLASS}$) as the standard error of these 100 realizations (i.e., the $SE_{biomass}$ term in Equations 3 and 6 below).

2.3.4. Details on carbon density assignments for other carbon pools (not AG) in tree dominated-landscapes.

FIA estimates of total live tree and standing dead tree biomass are derived from aboveground live tree equations (Woudenberg et al. 2010, Domke et al. 2011). Carbon stored in understory vegetation, coarse woody debris, litter and soil are generated from models based on geographic area, vegetation type, and in some cases, stand age (Woudenberg et al. 2011, Domke et al. 2011). These differences in the nature and source of the FIA data required different assignment procedures.

Assignment of total live tree biomass to Landfire classes used the approach described for AG. Linear transfer equations were fit as function of EVT, EVC, and EVH following the same logic and statistical criteria (Table S3). We applied the same simulation procedure to obtain a first-approximation of the uncertainty. However note that the relationship between mean and standard error in plot-level biomass (Figure 1) was based on AG not total live biomass.

Assignment of total standing dead tree biomass to Landfire classes followed the same overall approach described for AG but with two important differences. For the database used in this analysis (FIADB Version 5.1), standing dead tree biomass was estimated as if they were live trees (Domke et al. 2011). Without discounting for structural loss and wood decay, this FIA estimate admittedly overestimates the carbon density of standing dead trees (Domke et al. 2011). Given this bias, we limited our analysis. We developed assignments only at the coarser scale of vegetation classification, namely subclass. Specifically, we fit linear transfer equations as functions of subclass, EVC, and EVH. We followed the statistical criteria as for AG. Since we had no basis to estimate plot-level estimates, we simply used the error of the transfer function as the measure of uncertainty (Table S4).

For the modeled carbon pools -- understory live vegetation (Table S5), coarse woody debris (Table S6) and litter (Table S7) -- we applied the same analytical approach as for standing dead trees. We did not include soil carbon in our analysis.

2.3.5. Calculating carbon density for shrub-dominated landscapes.

We assembled data from multiple sources to calculate carbon density by vegetation type for shrub-dominated landscapes. Our primary source was the public version of the Landfire reference database (LFRDB). This database classifies existing vegetation in NatureServe's Ecological Systems units (i.e., the same system used to derive Landfire EVT), estimates cover and height of the dominant lifeform, and reports biomass densities (based on fuel metrics) for different carbon pools. See the Landfire website <http://www.landfire.gov/vegetation.php> for details. While the data can be extensive (e.g., 64 records for the Sonora-Mojave Creosotebush-White Bursage Desert Scrub, the most abundant shrub type in California), it is neither a comprehensive nor representative sample. It is also not spatially specific. Thus we could not link plot records to 2008 Landfire results as we did with the FIA data for forests. In short, we did not have data of sufficient quantity and quality to support the regression approach applied to tree-dominated biomass classes.

Instead, we built the best possible AG estimates for the common shrub-dominated EVT’s in California. We augmented the Landfire vegetation database with a thorough compilation of shrubland biomass densities reported in the literature. We found 35 relevant publications that contained results for six EVT’s. However more than half (19) of the published results were for one type -- the Southern California Dry-Mesic Chaparral. Within an EVT, we assigned biomass densities by three shrub-height classes: 0 to 0.5 m tall; 0.5 to 1.0 m tall, and > 1.0 m tall. Ideally, we had sufficient data to estimate the mean AG for each EVT by shrub height category. When possible these assignments were supplemented and vetted by published values. Standard errors of the means served as the only measure of uncertainty. In total, we produced biomass density estimates for the 15 most abundant shrub-dominated EVT's that together accounted for 90% of California's shrublands. To ascribe densities to the uncommon types, we used the same data and procedures to estimate AG biomass densities at the coarse scale vegetation category of "class". These uncommon EVT's inherited the value of the coarser category

We used published root-to-shoot ratios (Mokany et al. 2006) to calculate belowground biomass from the AG estimates. Total shrub biomass was the sum of these two components. Total live shrub biomass was assigned the same error rate as the AG estimate. The Landfire vegetation databases include modeled values for live understory vegetation (grass and herbs in this case), coarse woody debris and litter. As we did for the tree-dominated landscapes, we included estimates of these pools (means and standard errors) in our biomass classes.

2.3.6. Calculating carbon density for herb-dominated and remaining landscapes.

While biomass densities can be derived for Landfire tree and shrub types from field inventories, Landfire grassland and other vegetation types do not have information of similar extent or suitability. Therefore, we employed NASA MODIS NPP to calculate biomass densities for non-woody vegetation types. We downloaded MODIS Terra Net Primary Production Yearly L4 Global 1 km data files (MOD17A3, Collection 55) for 2000 to 2010 from the Land Processes Distributed Active Archive Center <https://lpdaac.usgs.gov>. We produced mosaics of the four swaths that covered the state and re-projected the data to the same projection and extent as the Landfire data, except with a spatial resolution of 1 km. For the analysis area, we masked out MODIS pixels with cloud cover in any individual year.

We conducted spatial analyses of the MODIS NPP data to calculate the mean annual vegetation production from 2000-2010 for each class and the standard error of the mean. We calculated above- and belowground fractions using published root:shoot ratios (Mokany et al. 2006). Because most of the standing biomass resides in herbaceous vegetation in these Landfire orders, mean annual aboveground vegetation production is approximately equal to aboveground standing biomass.

2.4. Calculation of carbon stocks, stock changes, and uncertainties

Informed by our carbon density calculations, we combined the available Landfire vegetation types, height classes, and cover classes into 1,083 biomass classes (Table 1). Biomass densities and the standard errors associated with these estimates were assigned to each biomass class based on the value of the three Landfire variables following the procedures described in Section 2.3. Every pixel in the analysis area has a matching biomass class. In addition, we retained the NVCS order and IPCC land category associated with each biomass class (Table S8).

From the original Landfire files, we produced spatial data files of combined vegetation types, height classes, and cover classes and biomass classes for 2001 and 2008. Spatial analysis of the biomass classes provided the land area of each biomass class for each year. The carbon stock of the state ($c_{\text{California}}$, Mg) for a single year equals:

$$c_{\text{California}}^{\text{year}} = \sum^{\text{biomass classes}} f_{\text{C}} B_{\text{class}} A_{\text{class}}^{\text{year}} \qquad \text{(Equation 2)}$$

where f_{C} is the carbon fraction of biomass (0.47 g carbon [g biomass]$^{-1}$; McGroddy et al. 2004), B_{class} is the biomass density (Mg ha^{-1}) of a biomass class, and A_{class} is the land area (ha) of a biomass class.

To quantify the uncertainty of each estimate of $c_{\text{California}}$, we conducted a Monte Carlo analysis that evaluated uncertainty in the three variables in Eq. 2. These uncertainties came from four potential sources: (1) variation in the carbon fraction of biomass, (2) statistical variation in biomass allometric equations, (3) statistical error of inventory sampling, and (4) land cover classification error of the area of each class. We calculated 100 realizations of aboveground live carbon stock in 2001 and 2008:

$$\hat{c}_{\text{California}}^{\text{year}} = \sum^{\text{biomass classes}} \left(f_{\text{C}} + X_{f\text{C}}\text{SE}_{f\text{C}}\right)\left(B_{\text{class}} + X_{\text{biomass}}\text{SE}_{\text{biomass}}\right)\left(A_{\text{class}}^{\text{year}} + X_{\text{area}}\text{SE}_{\text{area}}\right) \qquad \text{(Equation 3)}$$

where the hat symbol "^" denotes the form of a variable that includes a modeled estimate of error, $X_{variable}$ is a random number (different for each variable) from a normal distribution with mean = 0 and standard deviation (SD) = 1, and $\text{SE}_{variable}$ = standard error of a variable. We estimated SE_{fC} from McGroddy et al. (2004) as 5% of the mean (0.0235 g carbon [g biomass]$^{-1}$). For forest and shrub biomass classes, $\text{SE}_{\text{biomass}}$ came from the results described in sections 2.3.3 and 2.3.5 and listed in Table S8. For wetlands, grasslands, and other natural land areas, $\text{SE}_{\text{biomass}}$ came from the spatial analysis of MODIS NPP. SE_{area} = 61% of the mean, from a Landfire program validation of Landsat-derived land cover against field-observed land cover (Landfire 2008).

The 95% confidence interval (CI) equals:

$$95\%\ \text{CI}_{\text{stock}} = \frac{c^{97.5} - c^{2.5}}{2} \qquad \text{(Equation 4)}$$

where $c^{97.5}$ and $c^{2.5}$ are the 97.5$^{\text{th}}$ and 2.5$^{\text{th}}$ percentiles, respectively, of the 100 realizations of $c_{\text{California}}$. The uncertainty is the 95% CI expressed as a fraction of the mean:

$$\text{Uncertainty}_{\text{stock}} = \frac{95\%\ \text{CI}}{c_{\text{California}}} \qquad \text{(Equation 5)}$$

The net carbon change (Δc_{net}, Mg) for the state equals:

$$\Delta c_{\text{net}} = \sum^{\text{biomass classes}} f_{\text{C}} B_{\text{class}} (A_{\text{class}}^{2008} - A_{\text{class}}^{2001}) \qquad \text{(Equation 6)}$$

We used the Monte Carlo methods of Gonzalez et al. (2014) for the analysis of net carbon changes. We calculated 100 realizations of the 2001-2008 gross carbon change of the research area:

$$\hat{c}_{\text{California}}^{2001\text{-}2008} = \sum^{\text{biomass classes}} \left(f_{\text{C}} + X_{f\text{C}} \text{SE}_{f\text{C}}\right)\left(B_{\text{class}} + X_{\text{biomass}} \text{SE}_{\text{biomass}}\right)\left(\left|A_{\text{class}}^{2008} - A_{\text{class}}^{2001}\right| + X_{\text{area}} \text{SE}_{\text{area}}\right)$$

(Equation 7)

Equation 5 gives the 95% CI of the gross carbon change. Uncertainty of carbon change equals:

$$\text{Uncertainty}_{\text{change}} = \frac{95\%\ \text{CI}_{\text{gross change}}}{\sum^{\text{biomass classes}} f_{\text{C}} B_{\text{class}} \left|A_{\text{class}}^{2008} - A_{\text{class}}^{2001}\right|} \qquad \text{(Equation 8)}$$

The 95% CI of the 2001-2008 net carbon change of the research area equals:

$$95\%\ \text{CI}_{\text{net change}} = \text{Uncertainty}_{\text{change}} \Delta c_{\text{California}}^{2001\text{–}2008} \qquad \text{(Equation 9)}$$

In the Monte Carlo analysis of the uncertainty of net carbon change, note three features: (1) equations 7 and 8 use the absolute value of the change in land cover area, (2) uncertainty is calculated using gross change, and (3) the 95% CI of net change is calculated after uncertainty. This method, developed in Gonzalez et al. (2014), avoids the unwarranted inflation of the uncertainty calculation associated with small changes in carbon. In the extreme case, as carbon change approaches zero (the denominator in equation 5), the estimate of uncertainty becomes infinitely large. The situation of having near zero values is rare when measuring carbon stocks – they are generally positive values far from zero. However stock-change assessments can return small values and the behavior of the equations near zero must be addressed. Our approach avoids the mathematical artifact associated with small values by calculating uncertainty as a function of gross change instead of net change. For example, in a simplified two-biomass class case in which one class has a net carbon change of +10 Mg and the second class has a net carbon change of -9 Mg, uncertainty is more accurately based on gross change (19 Mg) than net change (1 Mg).

We also used equations 2-9 to calculate carbon stocks, changes, and uncertainties of each IPCC land category, each NVCS vegetation order, the area of public lands, private lands, and the U.S. national parks in California.

To assess the accuracy of our aboveground live carbon estimates, we validated our results against three published assessments for forested landscapes in California. All three used LiDAR to directly sense structural features of the vegetation. All three calculated carbon densities from forest inventories to inform the LiDAR interpolations of carbon stocks. The sites included Sierran mixed conifer forests near North Yuba, CA (Gonzalez et al. 2010), coast redwood forests in Mendocino County (Gonzalez et al. 2010), and true fir forests near Truckee, CA (Chen et al. 2012). Given the demonstrated performance and precision of LiDAR-derived maps of forest carbon (Gonzalez et al. 2010), we considered the results from these studies as the "true" carbon stock estimate. We also compared our statewide aboveground live carbon estimates against three recent national-scale estimates of forest carbon (Blackard et al. 2008, Kellndorfer et al. 2012, Wilson et al. 2013). These efforts vary in their specific methodologies but all rely on a combination of moderate resolution remote sensing data and FIA plots to produce spatially explicit maps of carbon stores. Thus while these comparisons do not represent validations since there are no criteria to determine the "true" or best value, they do provide useful points of reference.

We analyzed the sensitivity of uncertainty of net aboveground carbon change to the values of each variable by repeating the calculation three times, each time setting the error terms of all but one of the three variables (carbon fraction of biomass [SE_{fC}], biomass densities [$SE_{biomass}$], remote sensing accuracy [SE_{area}]) to zero. In a second sensitivity analysis, we repeated the calculation three more times, each time setting the error term on only one of the three variables to zero.

3. RESULTS

The analysis area covered 337,300 km^2 in 2001, 83% of the 404,500 km^2 land area of the state (Figure 2). Landscapes dominated by perennial woody plants (i.e., trees and shrubs) constitute the vast majority of the analysis area (Table 2). The average aboveground live carbon density of the state is 27 ± 8 Mg ha^{-1} (Table 2). The highest carbon densities coincided with forest cover and structure (Figure 3, Figure 4). The 95% CI of aboveground live carbon showed similar spatial patterns (Figure 5, Figure 6) as the carbon densities (Figure 3, Figure 4) with values highest in the forests of the coastal ranges, the Klamath

Mountains, and the Sierra Nevada.

Between 2001 and 2008, the total carbon stored in the forests and rangelands of California decreased from 2,600 million metric tons of carbon (MMTC = 10^6 MgC) to 2,500 MMTC (Table 3). Aboveground live carbon decreased ~2% (Figure 7) and total carbon decreased ~4%. Given our estimate of uncertainty (95%CI = ± 26 MMTC), a stock change of 100 MMTC represents a statistically significant loss of carbon at an annual rate of approximately 14 MMTC y^{-1}.

In general terms, 61% of the loss was due to a reduction in the carbon stored per area (i.e., carbon density); the remaining 39% was due to a reduction of the analysis area. Average carbon density declined from 77 Mg ha^{-1} in 2001 to 75 Mg ha^{-1} in 2008; the analysis area declined by 5,200 km^2 (Tables 4, Table 5). Much of the reduction in carbon density can be attributed to the transition of almost 13,000 km^2 of shrub-dominated lands to herb-dominated lands. On average the carbon density of grasslands is only 20% of shrublands (Table 6, Table 7). The decrease in analysis area was almost entirely due to the conversion of natural lands to agriculture. For example, more than 1,900 km^2 of land classified as tree-dominated in 2001 was classified as pasture/hay in 2008. Nearly 2,000 km^2 of shrub and herb dominated lands transitioned to some form of croplands in 2008.

Our analysis of the change in NPP supports the results from the stock change assessment. An extension of the metabolic theory of ecology (Price et al. 2010) states that ecosystem NPP should scale with total ecosystem biomass (Kerkhoff and Enquist 2006). We found a small decrease in the live carbon pool between 2001 and 2008 (i.e., ecosystem biomass) and thus expect a small decrease in NPP. For the entire analysis area, the change in NPP (mean ± SD) between 2001 (average of 2000-2003) and 2008 (average of 2007-2010) was -1% ± 10% (Figure 8).

The carbon stock changes associated with these transitions are summarized in Table 8. Forests that remained forest during the period accumulated carbon slightly, while most carbon losses occurred from conversion of forest to other natural lands (mainly grasslands) and to human lands (mainly agricultural land, Table 8). As noted above, most of the decreases within the IPCC category of forests occurred in the NVCS shrub vegetation order (Tables 6 and 7). Carbon stocks decreased on both public (Table 9) and private (Table 10) lands. The 26 U.S. national parks in California conserve 5% of the aboveground live carbon in the state (Table 11).

For all three validation sites, the 95% CI range of our live carbon estimates encompassed the LiDAR-derived stock estimates (Table 12). In terms of magnitude, our mean estimate was 14% lower for mixed conifer forests; 46% higher for the coast redwood sites, and a near match (1% lower) for the true fir forest (Table 12). Comparisons of our statewide results with other remote sensing-derived estimates showed that the 95% CI range of our values encompassed the two most recently published estimates (Kellndorfer et al. 2012, Wilson et al. 2013), but was significantly lower than the oldest estimate

(Blackard et al. 2008, Table 13).

The error in the Landfire classifications is the largest contributor to the uncertainty associated with our estimate of stock change (Table 14). If we assumed no error in the Landfire classification, the uncertainty of the estimate declines from 21% to 16%. However all three sources of error (carbon fraction, biomass estimation, and Landfire classifications) are important. Even the smallest source (carbon fraction) results in an absolute uncertainty in the stock change of almost 2 MMTC of aboveground live carbon.

4. DISCUSSION

The results from this stock change assessment indicate that the carbon stored in the forests and rangelands of California decreased by approximately 14 MMTC y^{-1} between 2001 and 2008. Our analysis of the uncertainty associated with this result supports that conclusion that the decrease is a statistically significant change. The validations of our live carbon stock assessments (Table 12), the consistency of NPP trends with theoretical expectations (Figure 8), and the close match with the most recent, published estimates of the total carbon pool in California (Table 13) attest to the robustness of the methodology.

A decrease of 14 MMTC y^{-1} contradicts the expectations of the Air Resources Board and the interagency technical committee. These expectations were informed by previous reports -- all but one concluded that the amount of carbon stored in the forests and rangelands of California was increasing (Table 15). Understanding the reasons for the discrepancies is complicated by the fact that the analyses vary in the time frame examined, the land type definition, and the methods used to calculate carbon flux (Table 15). For example, there are four different definitions of forests. Robards et al. (2010) used the FIA definition; Zheng et al. (2012) used NLCD; Brown et al. (2002) used the California Wildlife Habitat Classification (CWHR) and we used the Landfire definition. This lack of consistency prevents a one-to-one comparison of results. Furthermore, the variation in methods introduces logical mismatches. For example, Robards et al.'s (2010) modeling analysis does not consider any changes in forest extent yet land cover transitions accounted for 39% of the loss we observed. When Brown et al. (2002) conducted their analysis, the available inventory data was limited to northern and central regions of the state. Despite these complications, one difference with our results is clear – we estimated lower net carbon accumulation of tree-dominated ecosystems in California than previous reports.

The aboveground live carbon density of tree-dominated lands that remained tree-dominated barely increased from 2001 to 2008 (0.6%, Table 7). Carbon increment in forests is the balance between growth and mortality. Since we measured net changes we cannot parse growth gains from mortality losses. However two lines of evidence suggest that productivity of California's forests may be slowing. A recent report from the US Forest Service notes that the total carbon ecosystem pool in the National Forests of California has been declining since 2000 (USFS 2013). And in old (200+ years old), undisturbed forests across California, tree mortality rates have increased since 2001 (van Mantgem et al. 2009, Supplement). At the same time, we suspect that our reliance on Landfire vegetation layers limits the resolution at which we can detect tree growth, particularly for mature forests where the trees are taller. The span of the Landfire height categories increases with increasing height. For example at the short end, the height categories range only 5 m (EVH = 5 to 10 m) but at the upper end, it spans 25 m (EVH = 25 to 50 m). It takes a large absolute increase in forest height to detect change at the tall end. Over a relatively short interval, such a large change is unlikely to occur.

In general, our method likely underestimates live tree carbon densities for the most carbon dense forest types in California. The span of the height categories described above is one reason. Positive skew in the distribution of forest heights develops in the taller categories. For example, the mean height is greater than the median height for the 111 coastal redwood forests plots with Landfire forest heights from 25 to 50 m – an indication that there are proportionally more plots at the short end of the span than at the tall end. Thus the overall mean biomass for this category is weighted toward the shorter, lower biomass plots. Our decision to choose transfer models based on information criterion (i.e., AIC) and not fit (i.e., R^2) priorities the most abundant data points. While model selection based on AIC ensures the generality of the estimates, it does not fully capture the contribution of the extreme values. Statewide the underestimate is on the order of 8% if we consider the FIA estimate as the true value. Specifically, the FIA estimate of live tree carbon density for forests in California is 154 Mg ha^{-1}. Our comparable estimate for tree-dominated lands was 142 Mg ha^{-1} (i.e., 8% less). While there are sophisticated statistical approaches to accommodate positive skew (e.g., robust statistics and quantile regression), only a refinement in the remote sensing of forest height would truly solve the problem.

In the development of this inventory, we made a concerted effort to quantify the uncertainty due to potential errors and variation of remote sensing data, allometric biomass equations, and other key components of natural land carbon estimation. Error analysis provides the essential information needed to interpret results produced from complex measurement and analytical procedures. In addition, quantifying the contribution of individual variables to uncertainty detects the “weak links” in the chain of methods, and thus identifies priorities for improvement. Our methods of error appraisal and propagation conform to IPCC guidelines (IPCC 2006, IPCC 2013b), follow best practices recommendations by ecosystem scientists (Yanai et al. 2012), and include recent innovations in estimating uncertainty associated with change detection (Gonzalez et al. 2014). However we still consider our efforts a first order approximation. In particular, we relied on a simple regression approach to estimate the uncertainty in FIA plot-level estimate of tree biomass (Figure 1). An absence of information (e.g., measurement error rates) and the enormity of the task (3,000+ plots, 160,000+ trees) precluded a more rigorous analysis of the error associated with FIA biomass estimates. In addition, carbon pools other than live trees had little to no information on the error rates associated with the biomass calculations and thus we simply did not include this source of error.

Carbon decreases from wildfires were visible in the spatial analyses of Landfire (Figure 7) and the MODIS NPP (Figure 8) data. Close-up views of the Landfire results showed fire scars and timber harvesting areas (Figure 9). Most of the estimated decreases occurred in conversion of shrub ecosystems to grassland, mainly in fires in central and southern California chaparral and in conversion to agricultural land across the state. Forests that remained forests from 2001 to 2008 sequestered carbon, but not enough to balance the decreases in other ecosystems.

Redwood, Sequoia, Kings Canyon, and Yosemite National Parks conserve carbon at relatively high carbon densities. While public lands cover 60% of the area of natural lands, they accounted for only half of the carbon emissions. So, private lands accounted for a disproportionate share of carbon decrease. However this evaluation is based only on stock change and does not include life cycle considerations of harvested wood products.

Our results provide the first spatial estimates of vegetation carbon changes and uncertainties for the entire state and establish the beginning of a time series to track carbon dynamics in California ecosystems. The successful validation of our stock assessments (Table 12) alleviates concerns that practical demands of the inventory methodology undermine its utility. The theoretical consistency with NPP trends (Figure 8) and the close match to the most recent statewide forest carbon assessment (Table 13) further builds confidence in our approach. However it is important to recognize the limitations. The ability of Landfire to track vegetation growth warrants further investigation. There are large uncertainties associated with our estimates, particularly at the finer spatial scales (Table 12). Landfire is a national scale effort intended for applications at the regional scale, defined as areas millions of hectares in size (Rollins 2009). Analyses at finer scales must be undertaken with caution. There is also inherent circularity in our approach. Some of the data we use to fill biomass classes (e.g., FIA, MODIS) is also used to define the Landfire vegetation layers (Rollins 2009). This lack of independence could confound the error analysis and has the potential to compound mistakes. Landfire is a periodic analysis, (i.e., not annual) and does not specifically track disturbances. Thus stock changes must be assessed retrospectively. To understand the impact of disturbances such as fires and harvests on greenhouse gas emissions, other databases and additional analyses must be overlain on the Landfire-based stock assessment. In terms of data, the carbon stored in shrub-dominated lands is poorly quantified in comparison to tree and herb dominated lands. The FIA program delivers fundamental, high quality information on live tree biomass that is only becoming more valuable with time. Nevertheless, privacy restrictions on the exact spatial locations of the plots slows the pace of innovation. In contrast to live trees, the carbon stored in standing dead trees and downed wood is not directly measured in the FIA inventory (Domke et al. 2011). Yet the detritus carbon pool accounts for an important fraction of stored carbon and is expected to increase (Harmon et al. 2013). A companion project funded by the California Energy Commission is developing direct measures of standing tree carbon for the most common forest types in California. In general, carbon mapping and measurement is a rapidly advancing field with frequent improvements in both the technology and science. The modular framework of our approach is designed to accommodate improvements in data and processes as they become available.

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Table 1. Vegetation classes available in Landfire and used in this research.

	Vegetation Type (EVT)	Height Class (EVH)	Cover Class (EVC)
USA (Landfire)	706	57	73
California (Landfire)	163	39	54
Analysis area (Landfire)	136	19	34
Combined classes (this research)	53	14	18
Biomass classes (this research)			1083

Table 2. Distribution of land classifications in 2001 and aboveground carbon density.

	Area (%)	Mean (Mg ha^{-1})	95% CI (Mg ha^{-1})
California	100	27	8
IPCC land categories			
forests	80	35	8
wetland	1	1	4
grassland	8	1	2
other land	11	0.3	3
NVCS vegetation orders			
tree	37	67	18
shrub	43	5	3
herb	9	1	3
no dominant	5	0.2	4
non-vegetated	6	0.4	4

Table 3. Carbon stocks, changes, and uncertainties on forest land, wetlands, grassland, and other natural land areas of the State of California.

	Aboveground trees, shrubs, grass			**Total** above- and belowground, live and dead			**Sample**	
	Mean (10^6 Mg)	95% Confidence Interval (10^6 Mg)	Uncertainty (%)	Mean (10^6 Mg)	95% Confidence Interval (10^6 Mg)	Uncertainty (%)	(classes)	(10^6 pixels)
2001	920	± 240	26	2600	± 530	20	887	375
2008	900	± 260	29	2500	± 470	19	891	369
Stock Change	-21	± 5	21	-100	± 26	25	800	74

Table 4. Aboveground live carbon stocks, changes, and uncertainties across the State of California, by IPCC land category.

	2001			2008			2001-2008		
	Area (km^2)	Mean (10^6 Mg)	95% CI (10^6 Mg)	Area (km^2)	Mean (10^6 Mg)	95% CI (10^6 Mg)	Area (km^2)	Mean (10^6 Mg)	95% CI (10^6 Mg)
Forest	269 300	920	250	252 600	890	190	-16 700	-23	6
Wetland	2 500	0.2	1	2 000	0.2	1	-400	-0.04	0.1
Grassland	27 500	3	7	39 500	5	10	12 000	2	5
Other land	38 100	1	7	38 000	1	10	-74	-0.02	0.02
Total	337 300	920	240	332 100	900	260	-5 200	-21	5

Table 5. Total carbon stocks, changes, and uncertainties across the State of California, by IPCC land category.

	2001			2008			2001-2008		
	Area (km^2)	Mean (10^6 Mg)	95% CI (10^6 Mg)	Area (km^2)	Mean (10^6 Mg)	95% CI (10^6 Mg)	Area (km^2)	Mean (10^6 Mg)	95% CI (10^6 Mg)
Forest	269 300	2590	550	252 600	2480	490	-16 700	-110	28
Wetland	2 500	1.2	1.6	2 000	1.0	1.2	-400	-0.2	0.3
Grassland	27 500	17	16	39 500	25	20	12 000	8	9
Other land	38 100	6	4	38 000	6	5	-74	-0.01	0.01
Total	337 300	2600	530	332 100	2500	470	-5 200	-100	26

Table 6. Aboveground live carbon stocks, changes, and uncertainties, by National Vegetation Classification System order.

	2001			2008			2001-2008		
	Area (km^2)	Mean (10^6 Mg)	95% CI (10^6 Mg)	Area (km^2)	Mean (10^6 Mg)	95% CI (10^6 Mg)	Area (km^2)	Mean (10^6 Mg)	95% CI (10^6 Mg)
tree	124 700	830	190	124 000	830	230	-700	0.6	0.01
shrub	144 600	90	63	128 600	66	41	-16 000	-23	15
herb	30 000	3	7	41 500	5	12	11 500	2	5
no dominant	17 900	0.4	7	17 900	0.4	6	-19	~0	~0
non-vegetated	20 100	1	7	20 100	0.8	9	-0.06	~0	~0
Total	337 300	920	240	332 100	900	260	-5 200	-21	5

Table 7. Total carbon stocks, changes, and uncertainties, by National Vegetation Classification System order.

	2001			2008			2001-2008		
	Area (km^2)	Mean (10^6 Mg)	95% CI (10^6 Mg)	Area (km^2)	Mean (10^6 Mg)	95% CI (10^6 Mg)	Area (km^2)	Mean (10^6 Mg)	95% CI (10^6 Mg)
tree	124 700	2200	570	124 000	2180	450	-700	-16	4
shrub	144 600	390	230	128 600	290	190	-16 000	-95	66
herb	30 000	18	15	41 500	26	21	11 500	8	7
no dominant	17 900	2	2	17 900	2	2	-19	-0.003	~0
non-vegetated	20 100	4	5	20 100	4	4	-0.06	~0	~0
Total	337 300	2600	530	332 100	2500	470	-5 200	-100	26

Table 8. Carbon stock changes and uncertainties across the State of California, 2001-2008, summarized by IPCC land category transition.

	Aboveground live			Total		
	Mean (10^6 Mg)	95%CI (10^6 Mg)	Change (%)	Mean (10^6 Mg)	95%CI (10^6 Mg)	Change (%)
Forests remaining forests[1] (net change)	+21	6	+2	+29	7	+1
Forests to other natural lands[2] (net change)	-23	11	-83	-76	29	-77
Forests to human lands[3] (gross change)[4]	-17	4	NA	-49	12	NA
Other natural lands remaining other natural lands (net change)	-0.02	0.04	~0	-0.08	0.06	~0
Other natural lands to human lands (gross change)	-0.2	0.4	NA	-1	0.8	NA
California natural ecosystems (net change)	-21	5	-2	-100	26	-4

[1]The IPCC category of forests include tree and shrub dominated lands except those types classified as wetlands.

[2] Natural lands refer to the IPCC land categories of wetlands, grassland, and other land.

[3] Human lands refer to agricultural and developed lands.

[4] Net changes are calculated when all the transitions remain within the analysis area; Only gross change can be calculated for transitions that include lands outside of the analysis area (namely agricultural and developed lands). However the transition from human lands to natural lands was rare (<0.2% of the analysis area).

Table 9. Carbon stocks, changes, and uncertainties on public forest land, wetlands, grassland, and other natural land areas of the State of California (205 300 km^2).

	Aboveground trees, shrubs, grass			**Total** above- and belowground, live and dead		
	Mean (10^6 Mg)	95% CI (10^6 Mg)	Uncertainty (%)	Mean (10^6 Mg)	95% CI (10^6 Mg)	Uncertainty (%)
2001	550	150	27	1510	320	22
2008	540	130	24	1460	340	23
Stock Change	-10	2	21	-50	11	24

Table 10. Carbon stocks, changes, and uncertainties on private forest land, wetlands, grassland, and other natural land areas of the State of California (127 000 km^2).

	Aboveground trees, shrubs, grass			**Total** above- and belowground, live and dead		
	Mean (10^6 Mg)	95% CI (10^6 Mg)	Uncertainty (%)	Mean (10^6 Mg)	95% CI (10^6 Mg)	Uncertainty (%)
2001	370	92	25	1110	310	28
2008	360	75	21	1050	300	28
Stock Change	-10	3	23	-60	11	20

Table 11. Aboveground live carbon of the 26 U.S. national parks in California. Land area includes forest land, wetlands, grassland, and other natural land areas.

National Park	2001 Stock (10^6 Mg)	2001 95% CI (10^6 Mg)	2008 Stock (10^6 Mg)	2008 95% CI (10^6 Mg)	2008 Area (km^2)	2008 Carbon Density (Mg ha^{-1})	2001-2008 Change (10^6 Mg)	2001-2008 95% CI (10^6 Mg)	2001-2008 Area (ha)
Channel Islands	0.2	0.1	0.2	0.2	510	5	0.01	0.005	-29
Death Valley	0.6	0.8	0.6	0.7	13 300	0.5	0.01	0.01	~0
Joshua Tree	0.1	0.2	0.1	0.2	3 200	0.4	0.01	0.01	~0
Kings Canyon	4.9	2.0	4.9	1.6	1 800	27	-0.03	0.02	~0
Lassen Volcanic	3.6	2.2	3.6	1.9	420	86	-0.02	0.01	~0
Mojave	0.3	0.5	0.4	0.4	6 400	0.6	0.02	0.03	~0
Pinnacles	0.2	0.2	0.2	0.1	110	20	~0	~0	-10
Point Reyes	0.9	0.5	1.0	0.6	230	42	0.09	0.06	~0
Redwood	7.2	3.9	6.9	3.3	430	160	-0.29	0.27	-70
Santa Monica	0.8	0.4	0.8	0.4	500	16	-0.02	0.01	-110
Sequoia	7.3	2.9	7.4	2.9	1 600	45	0.12	0.06	~0
Yosemite	16.2	6.9	16.1	6.4	3 000	54	-0.08	0.03	~0
Others	2.1	0.7	2.1	0.7	590	36	0.02	0.01	-34
All	44.5	13.8	44.4	13.5	32 140	14	-0.15	0.05	-250

U.S. National Parks in California: Cabrillo National Monument, César E. Chávez National Monument, Channel Islands National Park, Death Valley National Park, Devils Postpile National Monument, Eugene O'Neill National Historic Site, Fort Point National Historic Site, Golden Gate National Recreation Area, John Muir National Historic Site, Joshua Tree National Park, Kings Canyon National Park, Lassen Volcanic National Park, Lava Beds National Monument, Manzanar National Historic Site, Mojave National Preserve, Muir Woods National Monument, Pinnacles National Park, Point Reyes National Seashore, Port Chicago Naval Magazine National Memorial, Redwood National Park, Rosie the Riveter WWII Home Front National Historical Park, San Francisco Maritime National Historical Park, Santa Monica Mountains National Recreation Area, Sequoia National Park, Whiskeytown National Recreation Area, Yosemite National Park

Table 12. Validation of aboveground live tree carbon density estimates against values from LiDAR interpolations of field-derived estimates.

	Area (ha)	Carbon density (Mg ha^{-1})	95% CI (Mg ha^{-1})
Sierran Mixed Conifer (North Yuba)	5800		
Gonzalez et al. (2010)		140	1
This research		120	70
Coast Redwood (Mendocino)	5900		
Gonzalez et al. (2010)		82	1
This research		120	80
True Fir (Truckee)	3500		
Chen et al. (2012)		74	NA
This research		73	32

Table 13. Comparison of aboveground live tree carbon estimates for the State of California with other spatial estimates. Note that the difference in spatial resolution generates slight differences in total surface area for Blackard et al. (2008) and Wilson et al. (2013).

	Years	Spatial Resolution (m)	Area (km^2)	Carbon (10^6 Mg)	95% CI (10^6 Mg)
Wilson et al. 2013	2000-2009	250	178 000	850	-
This research	2008	30	172 000	840	250
Kellndorfer et al. 2012	1999-2002	30	119 000	970	-
This research	2001	30	119 000	800	220
Blackard et al. 2008	1990-2003	250	116 000	970	-
This research	2001	30	115 000	730	210

Table 14. Analysis of the sensitivity of Monte Carlo estimates of the uncertainty of 2001-2008 change in aboveground live carbon to individual variable uncertainties. All results are uncertainties, calculated as the standard error/mean and expressed as a fraction (%) of the mean. Biomass allometric and inventory errors range from 1 to 120% for tree and shrub biomass classes and 86 to 770% for grassland, wetland, and other land. Higher uncertainties occur in classes with very low biomass densities and high spatial variability.

Estimate	Carbon fraction of biomass	Biomass allometric and inventory errors	Landfire classification error	**California 2001-2008 carbon change**
Best estimates of error	5	1 to 770	61	**21**
Assuming error only in carbon fraction	5	0	0	**9**
Assuming error only in biomass	0	1 to770	0	**11**
Assuming error only in Landfire	0	0	61	**15**
Assuming no carbon fraction error	0	1 to 770	61	**18**
Assuming no biomass error	5	0	61	**17**
Assuming no Landfire error	5	1 to 770	0	**16**

Table 15. Summary of recent efforts to estimate carbon flux for forests and rangelands in California. Positive flux estimates represent losses from the ecosystem; negative values represent gains. See text for explanation of land type definition and method.

Source	Pool	Date	Land type: Definition	Area (km^2)	Method	Stock (10^6MgC)	Flux Estimate (10^6MgC y^{-1})
Robards 2010	Live tree	2001-2010	Forest: FIA definition	134 567	Inventory/Growth and Yield Model	1,391	-8.3
This study	Live tree	2001-2008	Forest: Landfire tree-dominated	124 700	LULC/Inventory	1,050	0.02
Zheng et al. 2012	All except soil	1992-2001	Forest: NLCD definition	98 998	LULC/Growth projections	NA	-15.7
Brown et al. 2004	All except soil	1994-2000	Forest: CWHR	NA	LULC/Inventory	NA	-2.0
This study	All except soil	2001-2008	Forest: Landfire tree-dominated	124 700	LULC/Inventory	2200	0.02
Brown et al. 2004	All except soil	1994-2000	Rangeland: LCMMP	NA	LULC/Inventory	NA	-0.05
This study	All except soil	2001-2008	Rangeland: Landfire shrub-dominated	144 600	LULC/Inventory	390	13.6
Potter 2010	All	1990-2004	All lands	408 704	Remote Sensing/Ecosystem Model	2,516 (woody component)	-24 to 15

Figure 1. Relationship between plot-level aboveground live biomass estimate and the standard error based on Monte Carlo propagation of measurement and allometric errors. Results from 302 forest plots from a variety of forest types.

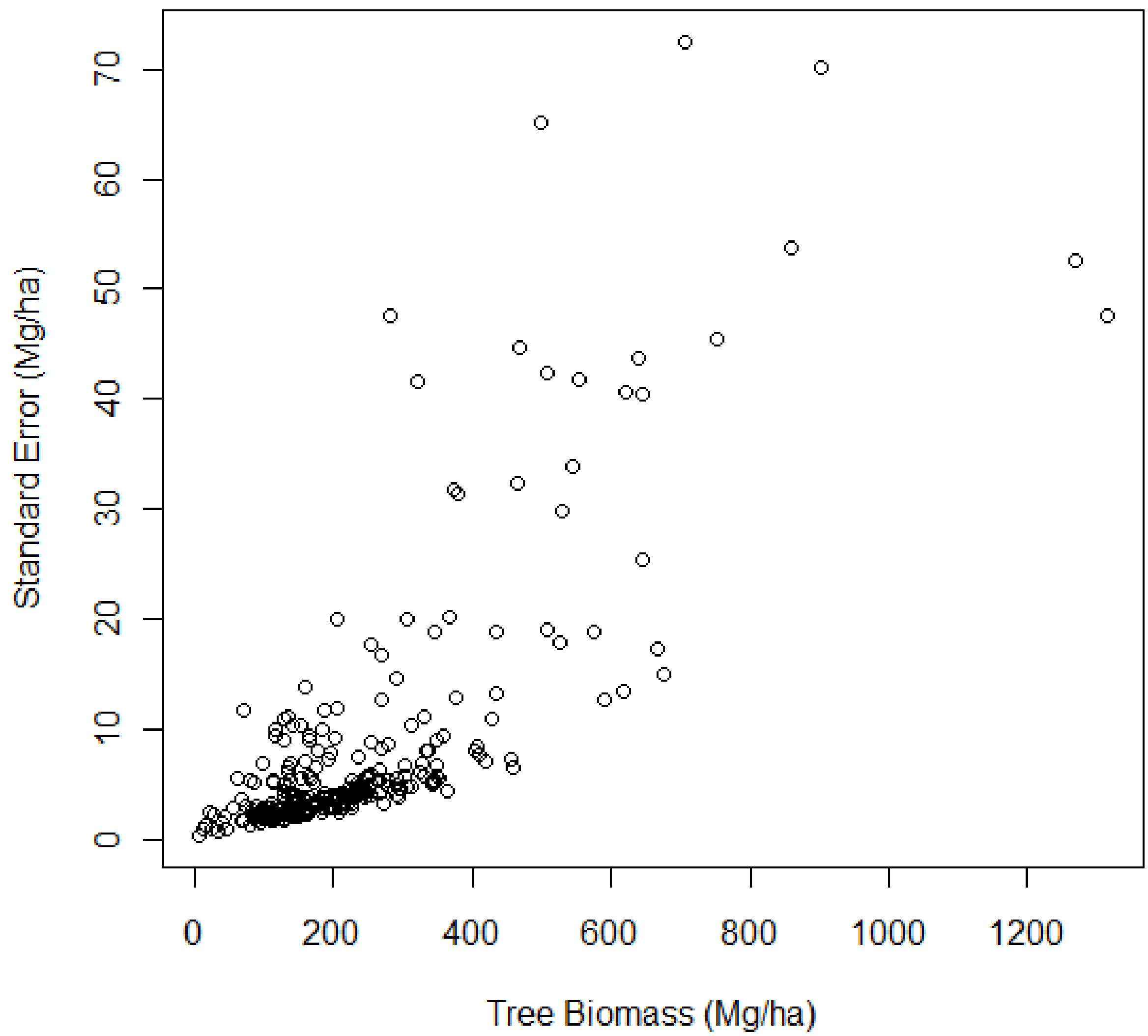


Figure 2. Land cover categories based on 2008 Landfire product.

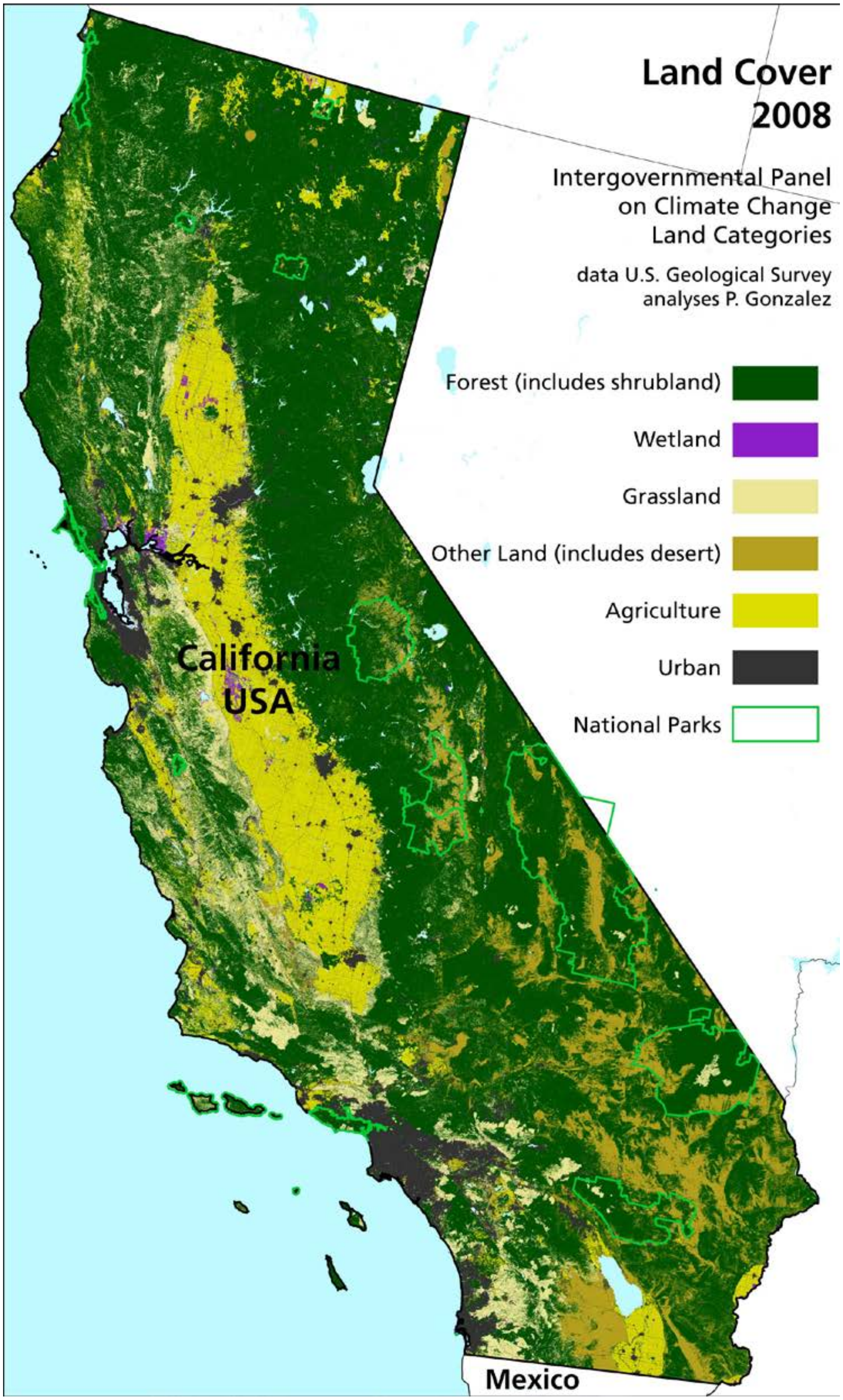


Figure 3. Carbon density of aboveground live vegetation in California in 2001.

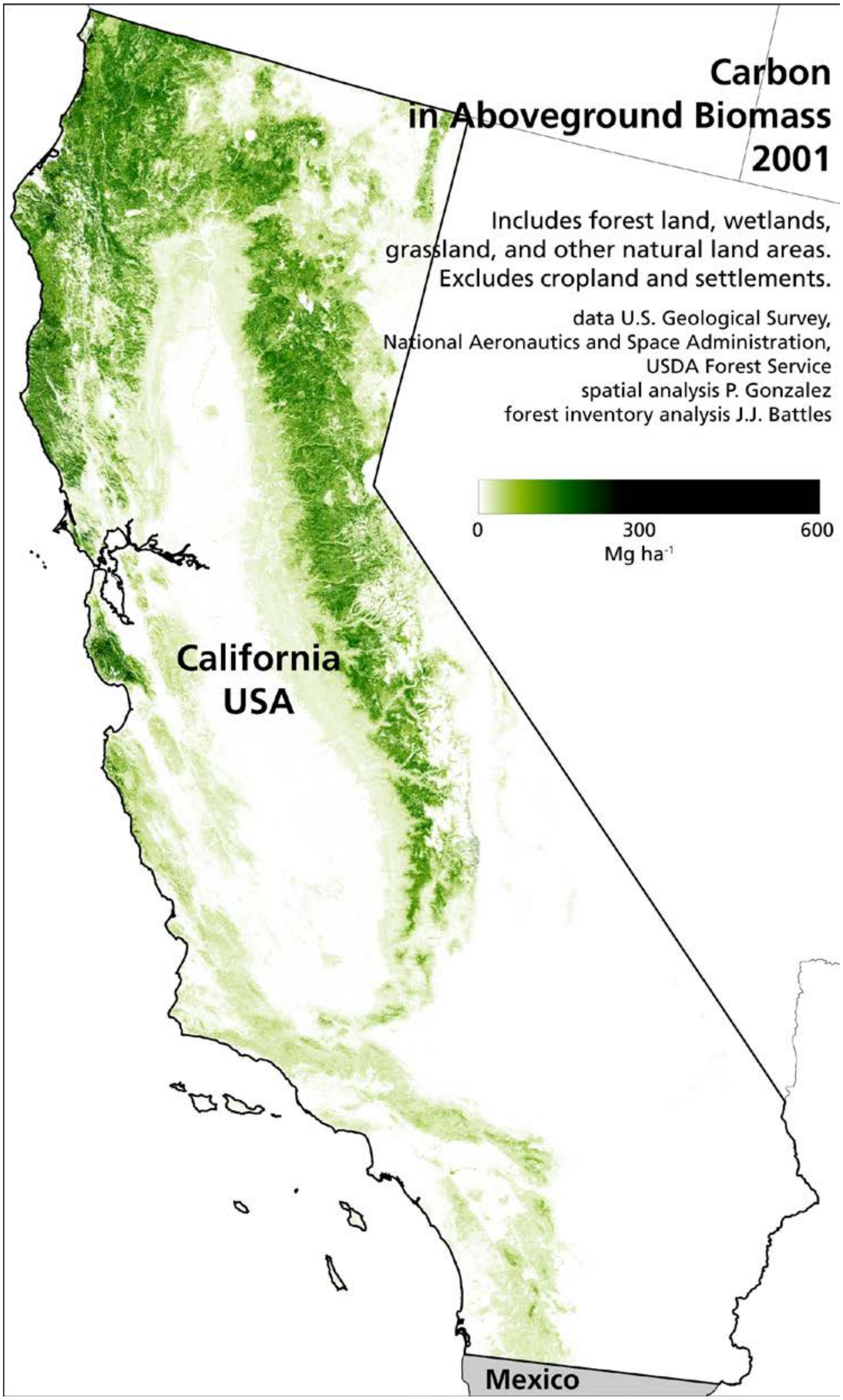


Figure 4. Carbon density in aboveground live vegetation in California in 2008.

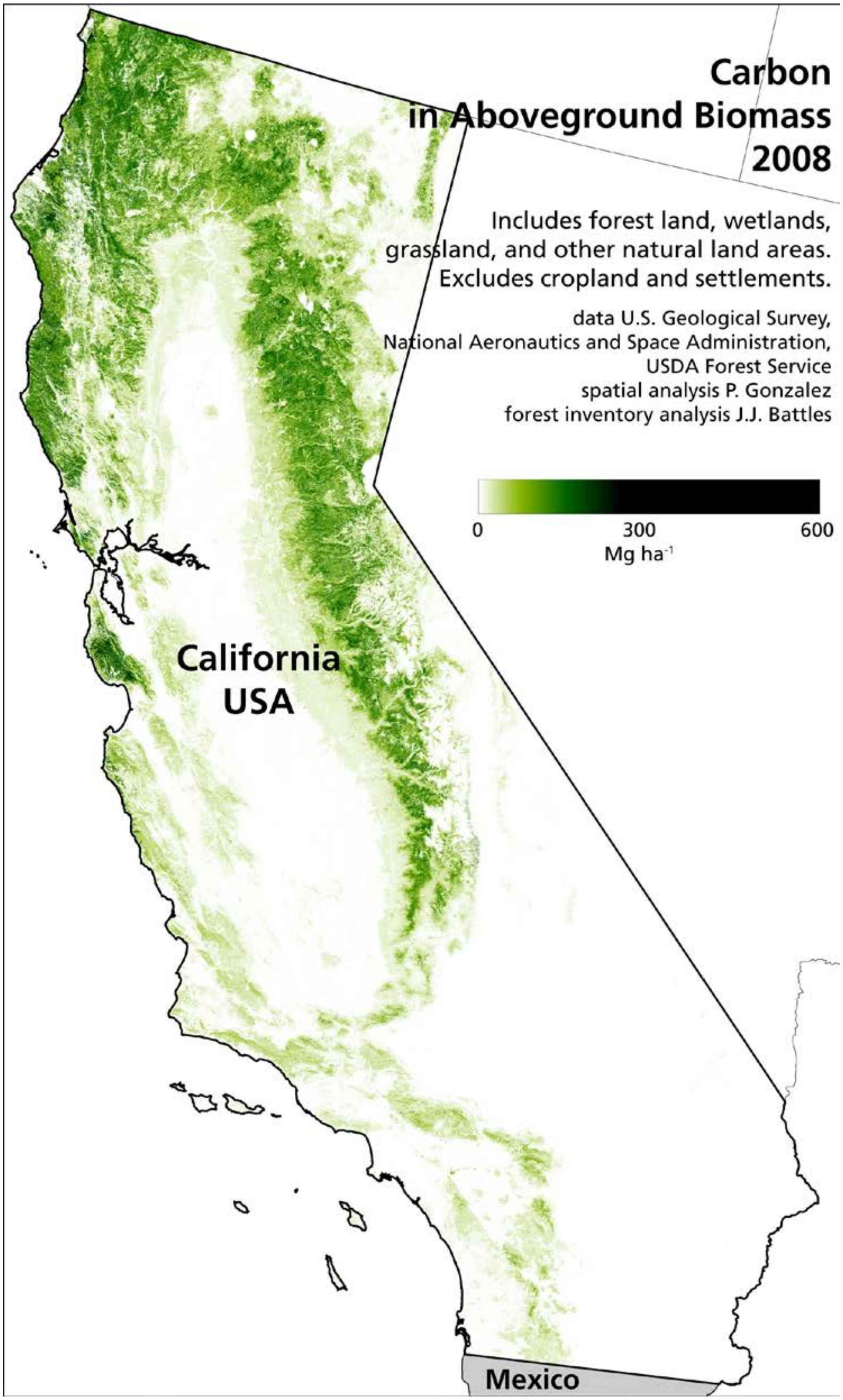


Figure 5. Distribution of first-order approximation of uncertainty associated with carbon density estimates calculated for California in 2001.

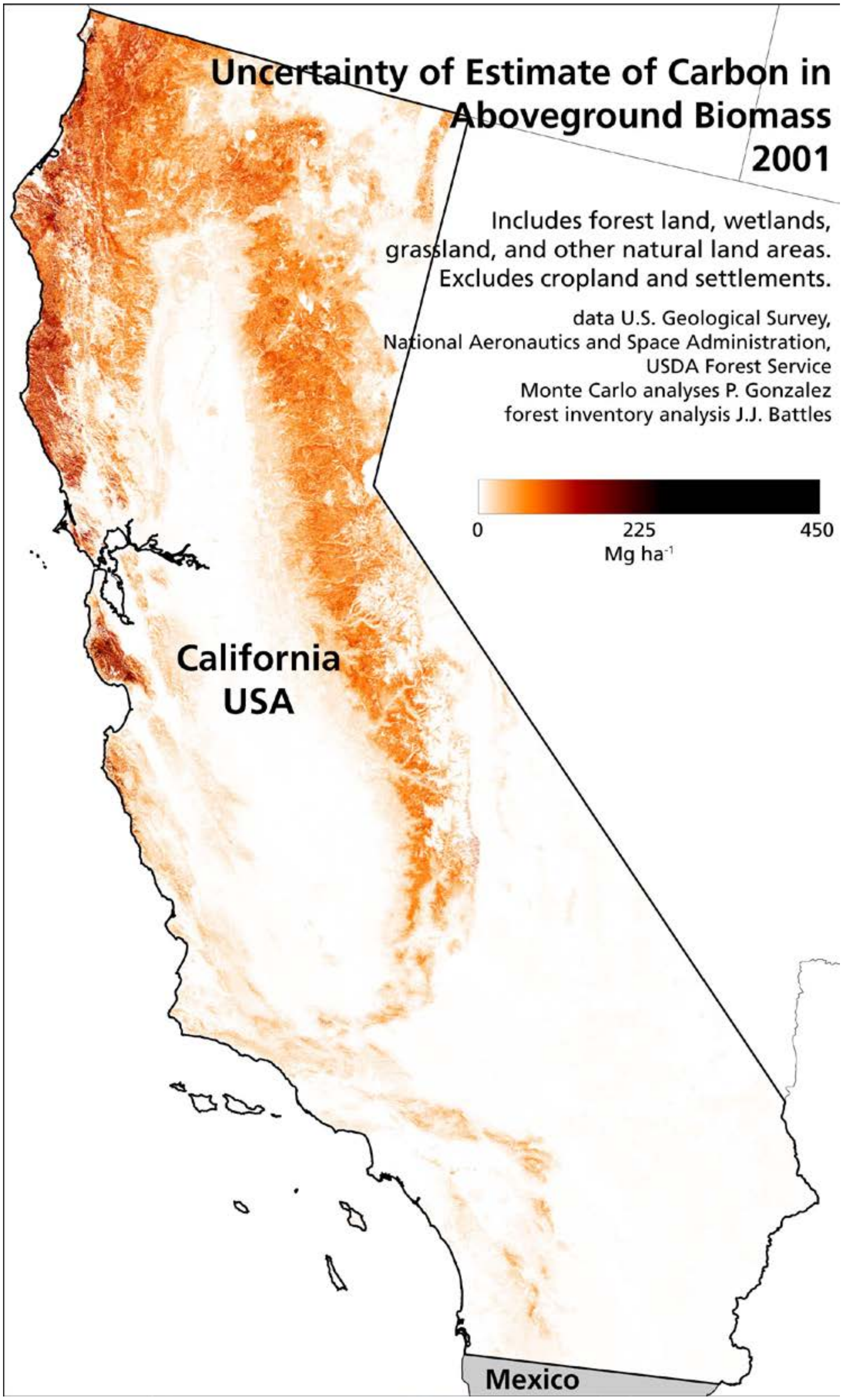


Figure 6. Distribution of first-order approximation of uncertainty associated with carbon density estimates calculated for California in 2008.

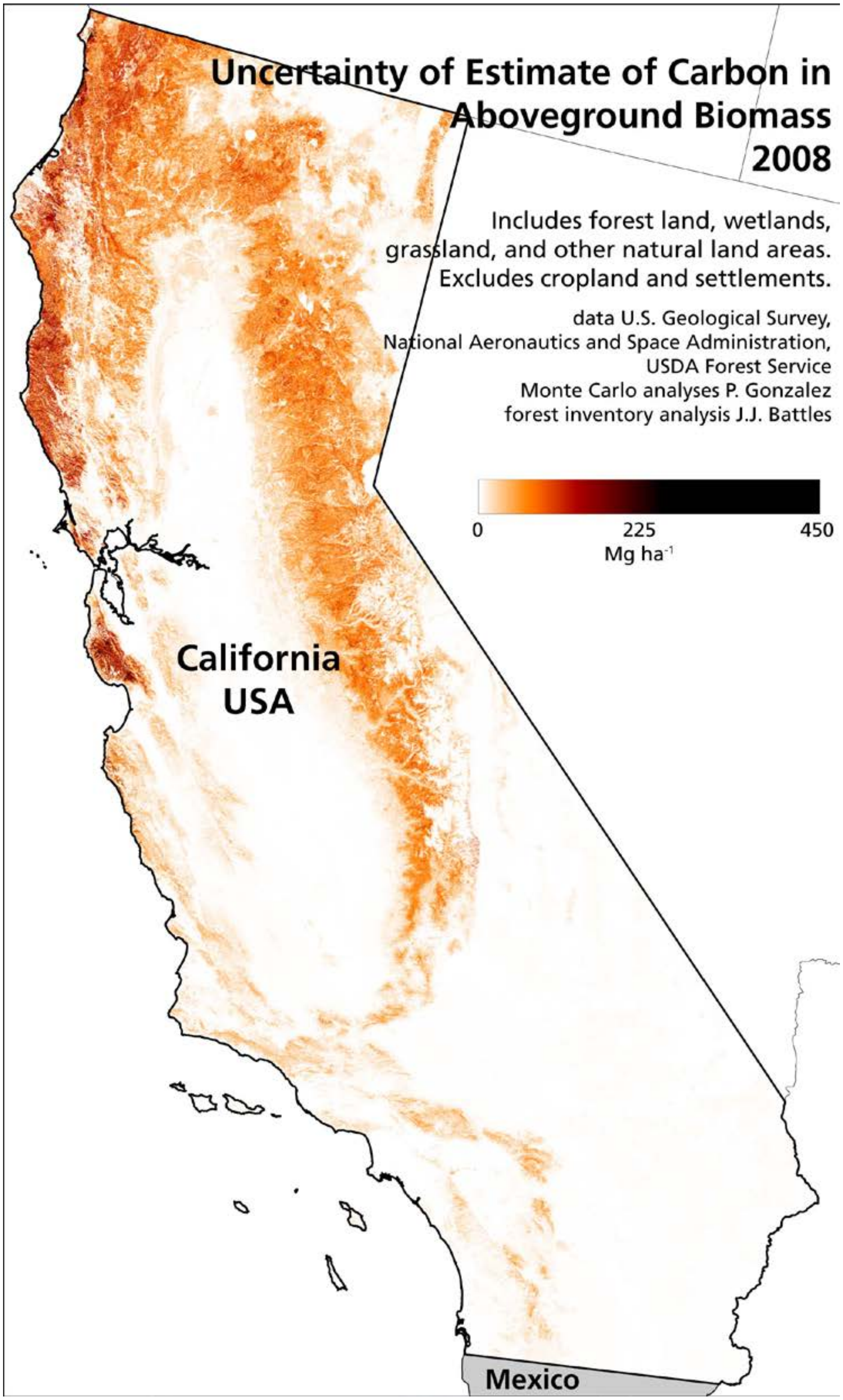


Figure 7. Changes in carbon density for aboveground live vegetation in California between 2001 and 2008.

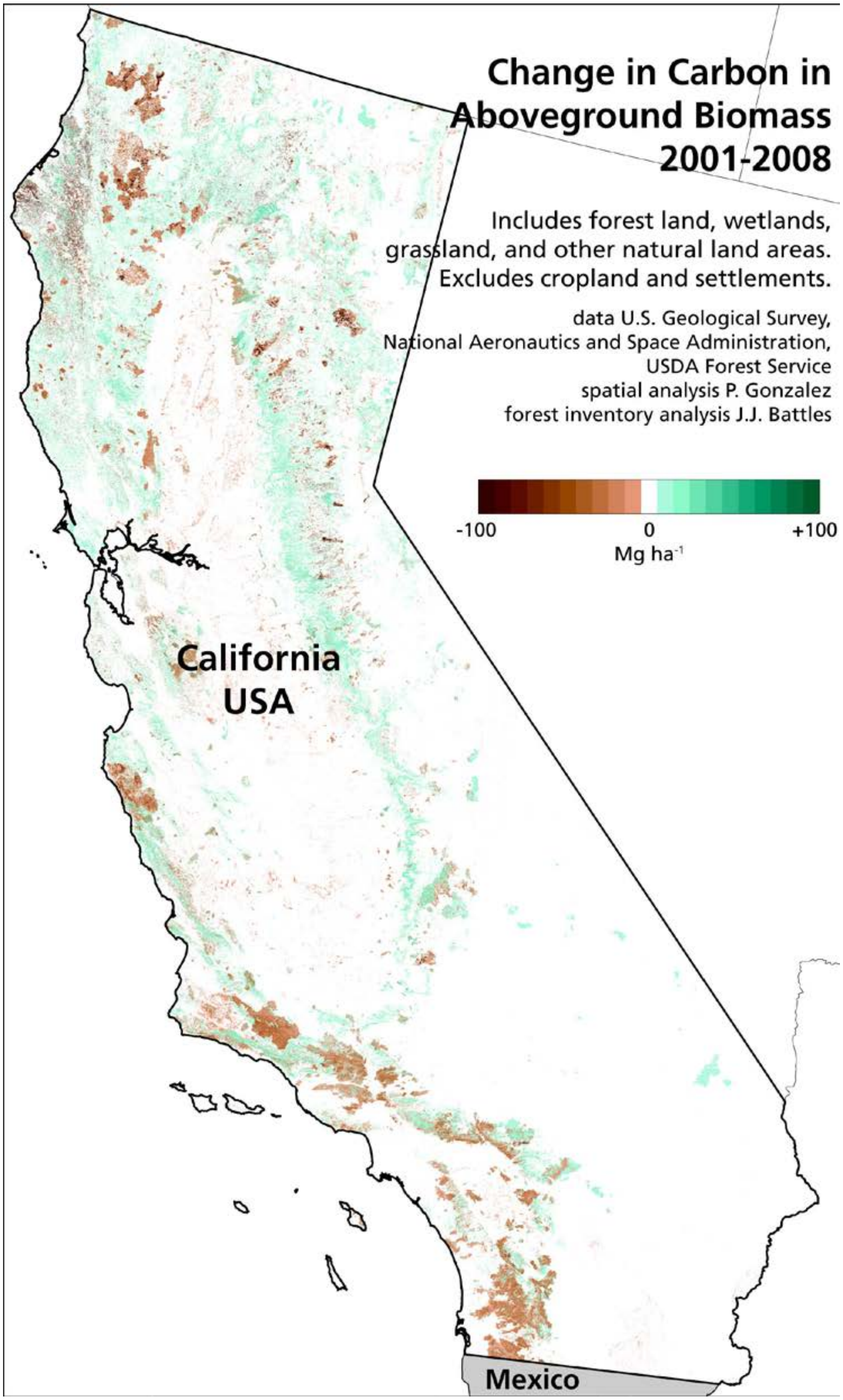


Figure 8. Changes in net primary productivity between 2001 and 2008.

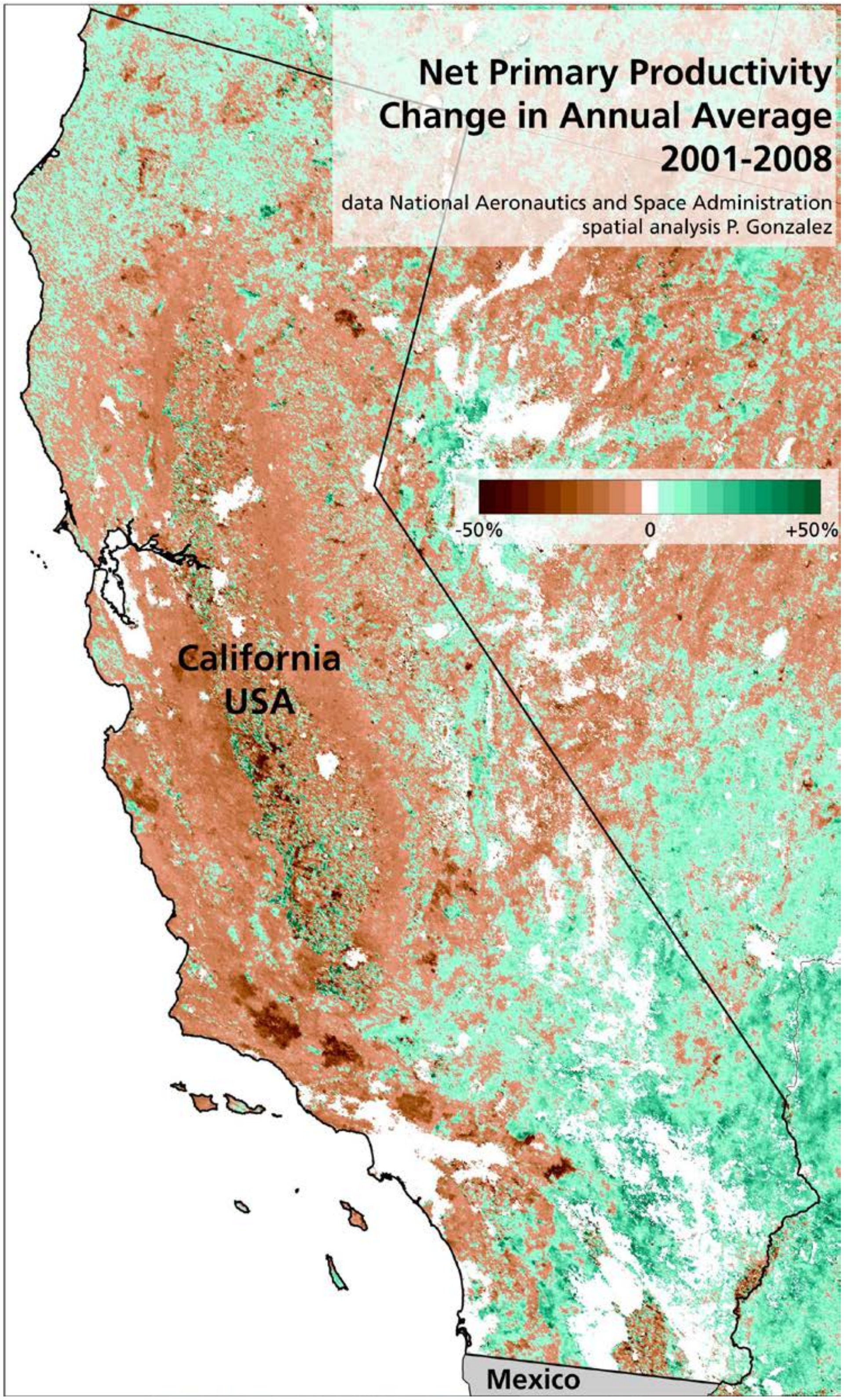
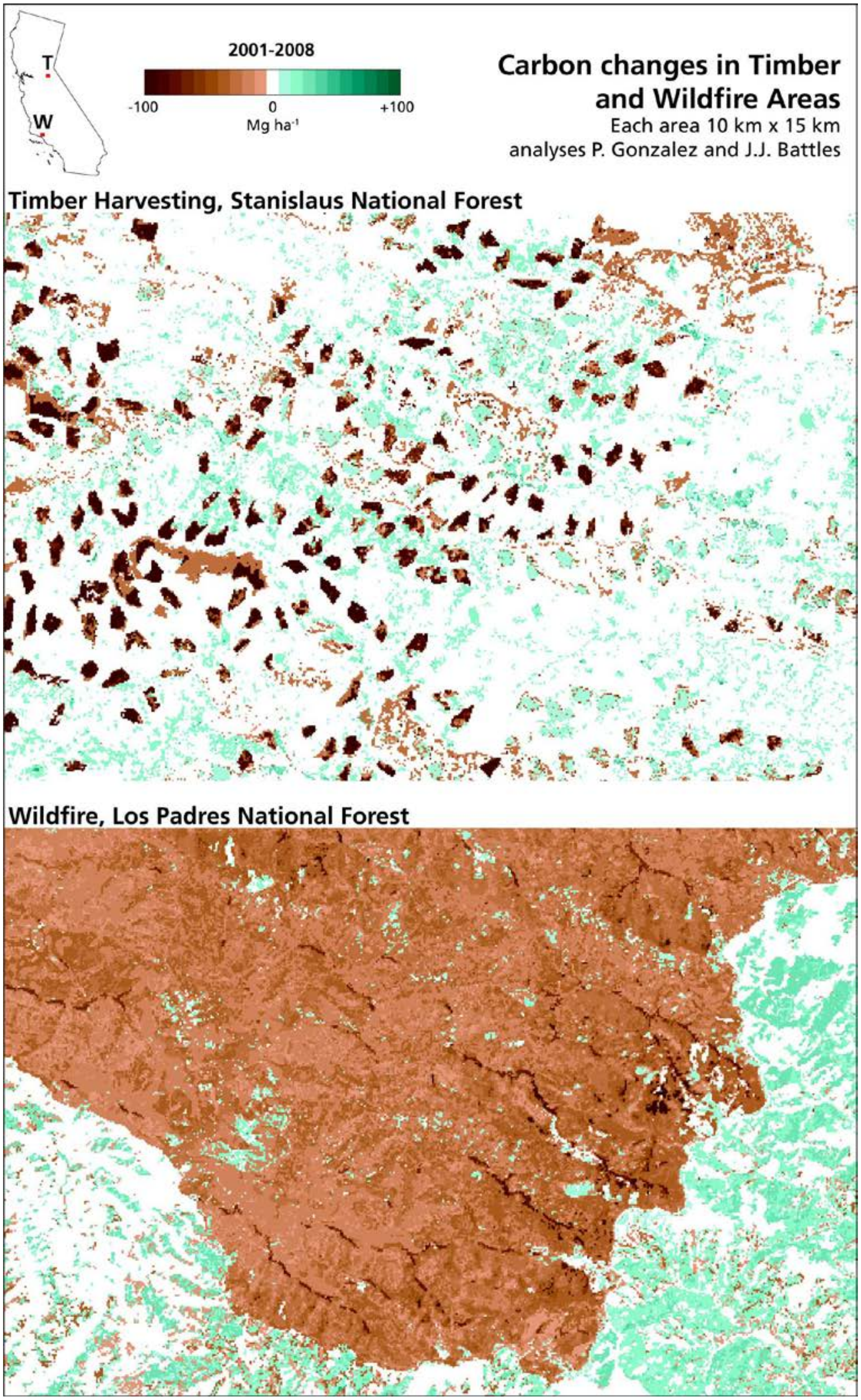


Figure 9. A close-up example of changes in carbon densities between 2001 and 2008 in areas impacted by timber harvests and wildfires.



Appendix 1. Using field data to assess model predictions of surface and ground fuel consumption by wildfire in coniferous forests of California

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Key Points

- Measured fuel load immediately before and after six wildfires
- Compared observed consumption to predicted for several fuel classifications
- Inaccurate fuel load predictions led to error in estimates of consumption

Abstract

Inventories of greenhouse gas (GHG) emissions from wildfire provide essential information to the state of California, USA, and other governments that have enacted emissions reductions. Wildfires can release a substantial amount of GHGs and other compounds to the atmosphere, so recent increases in fire severity may be increasing GHG emissions. Quantifying wildfire emissions, however, can be difficult due to inherent variability in fuel loads and consumption and a lack of field data of fuel consumption by wildfire. We compare a unique set of fuels data collected immediately before and after six wildfires in coniferous forests of California to fuel consumption predictions of the first order fire effects model (FOFEM), based on two different available fuel characterizations. We found strong regional differences in the performance of different fuel characterizations, with FOFEM overestimating fuel consumption to a greater extent in the Klamath Mountains than in the Sierra Nevada. Inaccurate fuel load inputs caused the largest differences between predicted and observed fuel consumption. Fuel classifications tended to overestimate duff load and underestimate litter load, leading to differences in predicted emissions for some pollutants. When considering total ground and surface fuels, modeled consumption was fairly accurate on average, although the range of error in estimates of plot-level consumption was very large. These results highlight the importance of fuel load input to the accuracy of modeled fuel consumption and GHG emissions from wildfires in coniferous forests.

Keywords: fuel consumption, wildfire emissions, fuel load model, greenhouse gas inventory, emissions modeling, California

1. Introduction

The State of California Global Warming Solutions Act of 2006 (AB 32) mandated the reduction of greenhouse gas (GHG) emissions to the 1990 level by 2020. Part of the state inventory of GHG emissions is the quantification of carbon emissions and removals by forests, grasslands, wetlands, and other natural lands. A growing forest acts as a carbon sink because it removes CO_2 from the atmosphere. On the other hand, a forest experiencing high mortality due to insects and fire can act as a carbon source due to CO_2 releases [*Canadell and Raupach*, 2008]. In California, wildfire emitted CO_2 at a rate of 24 Tg yr^{-1} in the period 2002-2006, approximately 6% of the amount of state fossil fuel emissions [*Wiedinmyer and Neff*, 2007]. As higher temperatures due to climate change contribute to increases in the frequency of large fires across the western U.S. [*Westerling et al.*, 2006] and the extent of high severity fires in the Sierra Nevada [*Miller et al.*, 2009], carbon emissions may also increase. The densification of forests in the absence of fire, particularly in those forest types historically associated with frequent fire, can increase net carbon stocks [*Collins et al.*, 2011]. However, often these increased stocks are less stable due to greater vulnerability to wildfire [*Houghton et al.*, 2000; *Hurteau and Brooks*, 2011; *Hurteau and North*, 2009; *Rogers et al.*, 2011].

While the importance of GHG emissions from wildfires is well recognized, emissions are difficult to measure with precision [*Wiedinmyer and Neff*, 2007]. Estimates of emissions typically rely on the use of stylized fuel characterizations to provide the necessary fuel inputs into fire effects programs. Errors in estimates of fire emissions can come from uncertainty in the burn perimeter [*French et al.*, 2011; *Urbanski et al.*, 2011], as well as estimates of fuel quantity and consumption [*Ottmar et al.*, 2008]. A large degree of uncertainty also arises from inaccurate emission factors, used to calculate emissions from biomass consumed [*Rosa et al.*, 2011]. Addressing these uncertainties associated with fuels not only requires accurate mapping of pre-fire fuel loads, but also quantifying the variation in fuel consumption across a wildfire [*de Groot et al.*, 2007]. The challenges of mapping and characterizing fuels contribute to uncertainties in emissions estimates [*Weise and Wright*, 2013]. In addition, the use of different fuel characterizations [e.g., *Ottmar et al.*, 2007] can lead to substantially different estimates of emissions [*Wiedinmyer et al.*, 2006].

Sampling in the same location before and after wildfire allows for accurate point measures of fire consumption and effects [*Campbell et al.*, 2007]. Fuel consumption directly correlates with emissions [*Seiler and Crutzen*, 1980], and is therefore a reliable surrogate for comparing the accuracy of emissions models. Unfortunately, knowing locations and actually measuring fuels in advance of wildfire is extremely difficult. As a result, much of the information on fuel consumption in wildfires comes from “fortuitous” burning of previously established field plots. Prescribed fires offer another, more dependable opportunity to quantify fuel consumption prior to and following fire. However, because prescribed fires generally burn under more moderate fuel moisture and weather conditions they do not exhibit the range in fire effects that is commonly observed in wildfires [*Collins et al.*, 2007; *van Wagtendonk and Lutz,* 2007].

In this study, we take advantage of a rare dataset that consists of vegetation and fuel measurements on the same plots taken just before and then immediately after six wildfires that occurred in California. We use this dataset to assess current approaches in predicting wildfire emissions. Our primary objective was to examine how fuel consumption predictions generated by the First Order Fire Effects Model (FOFEM) compared to fuel load changes observed in pre- and post-wildfire measurements. We also present the predicted emissions of compounds relevant to GHG inventories and air quality monitoring, both when using the field data as fuel inputs and when using stylized fuel characterizations. The choice of FOFEM is based on its use by the California Air Resources Board, the agency responsible for GHG inventories under AB 32. Our intent was to examine readily accessible or "out of the box" fuel characterizations that input into FOFEM and identify the one that best approximates observed consumption. We do not evaluate potential modifications to improve the performance of FOFEM itself (e.g., emission factors, combustion efficiency).

2. Methods

2.1 Field Sampling

The six wildfires sampled were located in the Klamath Mountains and Sierra Nevada, and burned mainly in conifer-dominated forest types (Figure 1, Table 1). Based on the relative differenced Normalized Burn Ratio (RdNBR) the six wildfires exhibited a range of fire effects. The Antelope and Clover fires were predominantly high severity, while the other fires were predominantly low severity (Table 1). All fires occurred in the summer or early fall (June-October). Field plots were located opportunistically based on anticipated fire spread. Measurements of dead and downed surface fuels, live surface fuels, ground fuels, and trees were taken in the same plots before and after burning by the Fire Behavior Assessment Team of the USDA Forest Service (USFS). Pre-fire measurements were generally taken 1-2 days prior to burning, and post-fire measurements were taken within one week (typically 1-2 days) after burning. Trees were sampled using a variable radius approach determined by wedge prisms. Average plot radius was 10 m, with a maximum of 49 m. Tree species, diameter at breast height (dbh, 1.37 m), and status (live/dead) were recorded for each tallied tree of dbh >2.54 cm. Litter, duff and downed woody fuels (1, 10, 100 and 1000 hour) data were collected along one or two transects in each plot using the planar intersect technique [*Brown*, 1974]. Fuel load calculations were adjusted using methods developed by Van Wagtendonk *et al.* [1996; 1998]. Tree seedling, shrub, and herb fuels were sampled on transects and fuel loads were quantified following methods in *Burgan and Rothermel* [1984]. Fuel components included in analyses were downed woody fuels, litter, duff, shrub/seedling and herbaceous. The amount of fuel consumed by the fire was calculated as the difference between pre- and post-fire data.

2.2 Modeled fuel consumption

Fuel consumption was modeled in FOFEM version 6.0 using the Consumed Emissions option [*Lutes et al.*, 2013]. FOFEM predicts woody fuel and litter consumption using the Burnup model. For duff, herbaceous plants and shrubs, FOFEM employs a decision tree to choose an appropriate consumption algorithm based on fuel model inputs [*Lutes*, 2012]. Based on the location of each plot (n=46), we assigned corresponding fuel inputs from two fuel characterizations: the Fuel Characteristic Classification System Fuelbeds (FCCS) [*Ottmar et al.*, 2007] and a coupled existing vegetation – fuel model link previously established by *Clinton et al.* [2006]. The latter fuel characterization uses the Society of American Foresters/Society for Range Management (SAF/SRM) fuelbeds. These fuel characterizations were of interest because they were both available for all six wildfires and both provide the necessary fuel inputs for FOFEM. Furthermore, these fuel characterizations are continuous coverages that encompass large spatial extents, offering an efficient and consistent way to quantify fuels and predict emissions across multiple fires.

In FOFEM, each SAF/SRM fuelbed has the option to select three fuel load levels: low, typical and high. For FCCS the typical fuel load level was the only option. This resulted in a total of four fuel characterizations per plot. Fuel moistures for FOFEM runs were based on the monthly average within each fire perimeter, developed from archival National Fire Danger Rating System dead fuel moisture data (available from – http://www.wfas.net). The decision to use coarser-scale fuel moistures (monthly vs. daily) is based on modeling procedures that are used for estimating criteria pollutant emissions for regional air quality modeling and emissions accounting under AB 32 (K. Scott, personal communication, California Air Resources Board).

In order to assess the performances of the four fuel characterizations (SAF/SRM low, typical, high, FCCS) with regard to emissions, we compared predicted emissions to those predicted using custom fuel inputs based on the pre-fire fuel loads for each plot. For these runs the daily fuel moisture for 10 and 1000 hour fuels was used, as determined from Remote Automatic Weather Station data corresponding to the area and day of burn for each plot. The day that each plot burned was determined from daily progression maps of each fire. As duff moisture was not available, its value was inferred as the corresponding value to the 10 and 1000 hour moistures used in FOFEM. The intent of this comparison was to investigate the extent to which predicted emissions using the coarser-scale inputs (fuel characterizations and monthly fuel moistures) over- or under-estimated those based on the finer-scale inputs.

2.3 Analysis of field data and fuel characterizations

The magnitude of difference between observed and predicted fuel consumption for each plot was assessed using regression trees. Regression tree analysis offers distinct advantages over traditional linear models because it can handle nonlinear or discontinuous relationships between variables, and high-order interactions [*Breiman*, 1993]. In addition, the hierarchical structure and identification of potential threshold values for independent variables is well suited for explaining ecological phenomena [*De'ath and Fabricius*, 2000]. The regression tree is constructed by repeatedly splitting the data into increasingly homogenous groups based on identified influential explanatory variables. We used the conditional inference tree technique in the PARTY library, within the statistical package R [*Hothorn et al.*, 2009]. This technique identifies influential explanatory variables using a partitioning algorithm that is based on the lowest statistically significant P value derived from Monte Carlo simulations. This minimizes bias and prevents over-fitting of the data, which is a common problem with regression trees [*Hothorn et al.*, 2006]. The significance level for each split was 0.05. Predictor variables examined were related to fuel and vegetation conditions, topography, and fire characteristics (Table 2). Topographic variables were determined from digital elevation models [*Gesch*, 2007; *Gesch et al.*, 2002] using ArcMap 10.0. The topographic relative moisture index (TRMI) was calculated using topographic position, slope, aspect and curvature [*Parker*, 1982]. Fire severity data was obtained from the USFS Remote Sensing Applications Center and classified using RdNBR [*Miller and Thode*, 2007]. Variables were calculated for a zone within a 40 m buffer around each plot, using the average for continuous variables and the median for categorical variables. Conditional inference trees were also used to examine the effects of plot attributes on observed fuel consumption. In both cases, individual fuel components (e.g., litter, duff, classes of downed woody fuels), as well as total fuel load, were assessed.

We assessed error associated with model predictions by calculating the percent difference from the field measured consumption, averaged by region. The average consumption observed in the field was subtracted from that predicted by models, and the resulting difference was then divided by the observed fuel consumption. Since this equality is a ratio of two random variables, the standard error was approximated using the Delta Method [*Rice*, 2007]. Standard error and 95% confidence limits were estimated using the NLMIXED procedure in SAS 9.3 [*SAS Institute Inc.*, 2011].

3. Results

3.1 Fuel loads

Differences in pre-fire fuel loads between fuel characterizations (SAF/SRM, FCCS) and field data varied by fuel component (Figure 2). All fuel characterizations tended to underestimate pre-fire litter loads. Pre-fire duff and 1000 hour fuel loads were generally over-estimated by fuel characterizations. This over-estimation was more pronounced for the SAF/SRM high and typical scenarios. These scenarios also over-estimated the 1-100 hour fuel load. Pre-fire shrub density was more variable in the field data, but the predicted values were fairly close to the median of the field measurements (Figure 2). None of the fuel characterizations accounted for areas with very high shrub load observed in the field data (8 out of 46 plots were outliers with shrub load

>35 Mg ha^{-1}). In general, median post-fire fuel loads were close to or equal to zero. However, observed post-fire duff loads were lower than predicted values for all fuel characterizations.

3.2 Consumption

The amount of fuel consumed was greater on average in the Sierra than in the Klamath region (Table 3). Correspondingly, the fuelbeds representing plots in the Klamath region tended to overestimate fuel consumption to a greater degree than those representing plots in the Sierra Nevada (Figure 3). There were no resulting splits in the regression trees assessing observed fuel consumption among plots, indicating that differences in actual fuel consumption could not be attributed to any plot characteristics we included in our models. This is likely due to the small number of plots included in the analysis. The difference in observed consumption between regions may be due to a greater amount of fuel remaining post-fire in plots in the Klamath region, rather than to differences in initial fuel load (Figure 4).

After accounting for regional differences, fuel characterization explained most of the difference in predicted consumption from the field data (Figure 3). Within the Klamath Mountains, the relationship of similar modeled fuel consumption to observed was explained entirely by the characterization type. FCCS and the low fuel load option for SAF/SRM had the closest prediction to the observed total fuel consumption, although the models still over-predicted consumption on average. In the northern and southern Sierra Nevada, among most plots differences were still attributable to fuel characterization type, but the relationship to modeled consumption was more complicated than in the Klamath. Drier plots (those with very low TRMI) tended to have much higher consumption than was predicted by all fuel characterizations. In addition, among the remaining plots, those with a cover type dominated by fir tended to have consumption over-predicted by the high fuel load SAF/SRM fuelbeds. Predictions of this fuel characterization were closer to field data for plots dominated by pine or oak. The average predicted fuel consumption based on FCCS and the low- and typical- variations of SAF/SRM fuelbeds were close to observed consumption regardless of forest type, although there was a fair amount of variation within this group (Figure 3). Although predictions based on these three fuel characterizations were not differentiated by the regression tree analysis, the low SAF/SRM had a lower median pre-fire fuel load than field measurements (Figure 4). In contrast the fuel load estimates of SAF/SRM typical and FCCS were closer to observed values, however these two characterizations did have slightly greater post-fire fuel load than was present in the field plots.

Within each region, all fuel characterizations had wide confidence intervals for the percent difference from field data in total fuel consumption (Table 4). As shown in the regression tree analysis, for plots in the Klamath bioregion, there was a large difference between different fuel characterizations in the percent difference from observed consumption, with fuelbeds within FCCS and the low fuel load version of SAF/SRM having closer predictions to observed consumption. Consumption was over-predicted on average using all fuel characterizations. In the Sierras, on average predicted consumption was closer to the field data. The high fuel load variation of the SAF/SRM fuelbeds resulted in too much predicted consumption, while the other fuel characterizations generally resulted in too little predicted consumption.

3.3 Emissions

Assessing data for both regions, comparisons of emissions predicted by FOFEM for the pre-fire field data to that predicted for the four fuel characterizations had a similar pattern to the comparisons of fuel consumption. For all emitted compounds the amount produced from flaming was greater in the field data than in the models (Figure 5, Table 5). Predicted CO_2 emissions for fuelbeds within FCCS were closest to the level predicted from the pre-fire field data (Figure 5). For CH_4 emissions, both the FCCS and low-SAF/SRM fuelbeds were close to that predicted using the field data. Among most emission species of concern to air quality, the same trends were present (i.e. SAF/SRM high and typical led to higher predicted emissions, while SAF/SRM low and FCCS were similar to predictions generated from the field data). An exception to this trend was NO_x; predicted NO_x emissions were greater in the field data than in all other models as this compound is only produced during flaming combustion (Table 5).

4. Discussion

Our study used a unique dataset to compare field measurements of surface and ground fuels consumption to that predicted by modeling. While this study provides valuable insight into fuel consumption from wildfire, a potential shortcoming is the opportunistic rather than designed nature of the field sampling. Although we treat plots as a random sample, they do not evenly represent the range of burn severity observed, particularly for some fires (Table 1). Field data were skewed towards representing lower fire severity areas (46% of plots), and therefore may not adequately characterize the consumption associated with higher severity burning (13% of plots). Despite this limitation, the work presented still addresses a critical area where knowledge is lacking. The only similar study we are aware of looking at forest data pre- and post-wildfire examined only one fire in which the pre-fire data was collected several (5-9) years prior to burn and did not contain pre-burn measurements of all fuel components [*Campbell et al.*, 2007]. It should also be noted that this study only provides information about emissions from ground and surface fuels using FOFEM. We did not address the contribution of canopy fuels to emissions, or compare effects of different consumption models, which can also affect emissions estimates [*French et al.*, 2011].

Discrepancies in predicted and observed fuel consumption tended to be due to the fuel models assigning a higher amount of fuel pre-fire than was measured in the field, with the post-fire fuel load being more similar to the measured data (Figures 2 and 4). This result agrees with *Keane et al.* [2013], who found poor agreement between several fuel characterizations, including FCCS, and a large dataset of fuel loads derived from Forest Inventory and Analysis plots. In particular, the fuel characterizations we tested tended to overestimate pre-fire duff and 1000 hour fuel loads, especially those from the high and typical SAF/SRM. Previous work looking at uncertainty in emissions estimates also found that inaccurate predictions of fuel consumption tend to be driven by error in estimates of pre-fire fuel loads [*Urbanski et al.*, 2011; *Wiedinmyer et al.*, 2006]. The problems associated with inaccurate characterizations of surface fuels are not limited to wildfire emissions modeling and can be attributed to their inherent spatial and temporal heterogeneity [*Hall et al.*, 2006; *Keane et al.*, 2012; *Keane et al.*, 2013] and the general inability of aerial imagery to directly detect surface fuel loads [*Jakubowksi et al.*, 2013].

In contrast to the general overestimation of pre-fire fuel loads, the fuel characterizations we tested estimated much lower pre-fire litter loads than that observed in the field plots. *Campbell et al.* [2007] similarly found that litter load was lower in FCCS fuel inputs than in pre-fire field data, attributing this discrepancy to differences in how litter and duff were defined. The fact that we found a consistent underrepresentation of litter loads coupled with a general tendency to overpredict duff loads across fuel models likely contributed to the differences observed in the predicted emissions of some compounds. As litter is mostly consumed in flaming combustion and duff tends to be consumed in smoldering combustion, which is less efficient, this discrepancy in pre-fire litter vs. duff loads can lead to inaccurate attribution of emissions (e.g., greater emissions of constituents associated with smoldering [particulates] rather than flaming [oxides of nitrogen]) [*French et al.*, 2011; *Hardy et al.*, 2001; *Sandberg et al.*, 2002].

One aspect of fuelbeds that characterizations cannot account for at current resolutions is the significant variability that exists within a fuelbed type [*Keane*, 2013]. As was found in this study, the range of fuel loads prior to burning is typically much greater than that available in simulations [*Weise and Wright*, 2013]. Fuel maps for mountainous terrain may be less accurate due to the effects of topography on fuel load variability [*French et al.*, 2011; *Jakubowksi et al.*, 2013]. In addition, fuel particle size classes vary at different spatial scales, and this scaling may also vary by cover type [*Keane et al.*, 2012]. It is difficult to capture realistic ranges in fuel loads with current modeling approaches, which tend to represent average conditions. This is reflected in the high standard errors and wide intervals of prediction accuracy for fuel consumption in all fuel classification types (Table 4). Perhaps building in stochastic variability or some type of dynamic association with other variables (e.g., topography, canopy cover) could be incorporated in future model development.

Based on the pre- and post-wildfire data collected, high variability existed in observed consumption as well as in pre-fire fuel loads. Total surface and ground fuel consumed ranged from 0% to 100%, with a mean of 68%. All plots showed evidence of burning, even those located within areas classified as unchanged by RdNBR., which is an acknowledged outcome for surface burns that leave the overstory unchanged [*Kolden et al.*, 2012]. Although the median litter found post-fire in field plots was zero, in many instances not all litter was consumed. In contrast, FOFEM predicted 100% litter consumption for all fuel models, representing more homogenous burning. When scaling up to assess total emissions from a wildfire, FOFEM results can be adjusted for patchy burns by weighting results by the percentage of area burned [*Lutes*, 2012]. However this could be problematic when using measures such as RdNBR where surface burn patterns may be obscured by the overstory canopy. The median post-fire duff load was also zero; however models typically predicted some duff remaining after fire. Differences in duff consumption have been linked to the influence of canopy cover on duff moisture [*Hille and Stephens*, 2005], at least for prescribed burns. Comparing models to results of prescribed fires, *Hollis et al.* [2010] also found greater variation in observed consumption than modeled consumption; models failed to represent the occurrences of extremely low or high consumption. Incorporating this variability in consumption is a challenge, however, failing to account for fire severity can lead to inaccurate estimates of wildfire emissions [*Veraverbeke and Hook*, 2013].

Shrub load was another highly variable fuel component that was generally misrepresented by the fuel characterizations tested. While overall shrub density has decreased in contemporary forests with dense overstories they do occur in fairly concentrated pockets when present [*Nagel and Taylor*, 2005]. The fuel models we tested generally predicted very low shrub load, which is representative of the majority (72%) of the plots we sampled. However, 17% of our plots had very high shrub density, corresponding with live fuel loads ranging from 38 to 210 Mg ha^{-1}. This demonstrates that patches of high shrub density that may occur within other cover types can contribute a significant proportion to the total fuel consumption and thus emissions, which may be overlooked by fuel classifications.

5. Conclusions

In order to account for wildfire emissions across large spatial scales agencies rely on wildfire emission models coupled with remote-sensing based fuel characterizations. Based on our results it appears that FOFEM coupled with either fuel classification type we analyzed (FCCS or SAF/SRM) can perform reasonably well for predicting surface and ground fuel consumption by wildfire. For total surface and ground fuel consumption, FCCS and the low fuel loading option for SAF/SRM performed very well in both regions on average. It should be noted that in the Sierra Nevada, the typical fuel load option for SAF/SRM also provided predictions close to actual consumption. Perhaps combining the fuel components compensated for fuelbed errors among different fuel load components (i.e. low predictions of litter load may have been compensated for by high predictions of duff load). While these models were fairly accurate on average, the confidence intervals associated with the percent accuracy in our dataset were very large. Therefore predictions at the level of an individual plot may err considerably, but when assessing a larger area the predicted consumption may be closer to what was observed in our data.

Among pine and oak dominated sites in the Sierra Nevada, the high fuel load SAF/SRM option also gave fairly accurate estimates of consumption. A limitation to our analysis is the lack of fuels data associated with oak-dominated cover types for SAF/SRM classifications in FOFEM. These fuelbeds are provided in FOFEM only as a customizable option with user-defined inputs, with “default” values of zero. We chose to run the model as it was (i.e. no fuel load prior to burn). Although only six plots in our dataset were categorized with an oak-dominated cover type under SAF/SRM, this still may have affected our results. Because of this limitation, when site-specific information is lacking, FCCS cover types may be preferable for generating estimates of emissions for oak-dominated areas.

The estimates of GHG emissions (CO_2 and CH_4) using FCCS or the low fuel load scenario for SAF/SRM fuelbeds were also close to that predicted using the field data as FOFEM inputs. Some differences existed for predictions of emissions of compounds more exclusively associated with either flaming or smoldering, particularly among the SAF/SRM classifications. FCCS fuelbeds had a higher estimated litter load than the those in the SAF/SRM characterizations and were therefore closer to the field data, so the emissions predicted using these fuelbeds were closer in general to those estimated using the field data.

Although California is one of the few states that require GHG inventories, interest in emissions accounting elsewhere is broad. Wildfires can contribute a substantial quantity of GHG emissions although the contribution is generally pulsed and unpredictable. While it is clear some error is associated with predictions generated from the modeling framework evaluated in this paper, it is important to understand how much error there may be and what potential adjustments can be made to minimize it. A better understanding of discrepancies between modeling efforts and wildfire effects can improve the ability of agencies to inventory GHG emissions.

6. Future Improvements

This work could be expanded on in the following areas:

- Collect additional field data to get a better representation of fuel consumption in different vegetation types (e.g., chaparral)

- Monitor sites burned by wildfire to investigate post-fire succession and fuel trajectories
- Expand the study to include field sampling in wildfires occurring on land burned in previous fires, to see how fuel consumption differs between previously burned and unburned areas

Acknowledgements

We are very grateful to Klaus Scott, California Air Resources Board for providing feedback on the data analysis and reviewing the manuscript. We would also like to thank the Fire Behavior Assessment Team (USFS), including N. Vaillant, for their work collecting and organizing the field data. Sylvia Mori at the USDA Forest Service, Pacific Southwest Research Station was consulted for statistical advice. Funding was provided by the California Air Resources Board, contract number 10-778.

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Table 1. Summary of fires sampled

Fire	Year	Region	Size (ha)	Severity	% of Area	Plots
Bake-Oven	2006	Klamath	26325	Unchanged	11.7	1
				Low	44.6	6
				Moderate	26.0	0
				High	17.6	0
Somes	2006	Klamath	6275	Unchanged	27.0	4
				Low	58.3	3
				Moderate	10.8	1
				High	3.9	0
Antelope	2007	N. Sierra	9037	Unchanged	5.3	1
				Low	13.1	0
				Moderate	28.3	5
				High	53.3	3
Ralston	2007	N. Sierra	3408	Unchanged	8.9	0
				Low	52.4	9
				Moderate	29.2	5
				High	9.5	1
Crag	2005	S. Sierra	6389	Unchanged	20.8	0
				Low	56.3	1
				Moderate	19.0	0
				High	3.9	0
Clover	2008	S. Sierra	480	Unchanged	21.9	0
				Low	13.0	2
				Moderate	22.6	2
				High	42.5	2

Table 2. Predictor variables used in regression tree analysis to explain differences between observed and predicted fuel consumption[a]

Variable Type and Description
General
Fuel input: (SAF/SRM-low, -typical, -high; FCCS)
Region: (Klamath, N. Sierra Nevada, S. Sierra Nevada)
Existing vegetation
Dominant type: (fir, pine, oak)[b]
Tree size class: (seedling, small, medium/large)[c]
Density class: (open, moderate, dense)[c]
Fuel moistures (%)
Duff: (20-40, x = 22.6)
10-hr: (6-10, x = 6.5)
1000-hr: (5-11, x = 7.9)
Topography
Elevation (m): (419-2657, x = 1355)
Slope (%): (2-84, x = 31)
Aspect (cosine transformed): (0-2, x = 1.0)
Topographic position: (lower-slope, mid-slope, ridge, flat)
TRMI: (5-51, x = 28.2)
Fire variables
Severity: (unchanged, low, moderate, high)
Distance-to-fire-edge (m): (12-1909, x = 523)

[a]Ranges and means (x) for continuous variables, and input levels for discrete variables are also reported.

[b]Based on Calveg regional dominance classes (http://www.fs.usda.gov/detail/r5/landmanagement/resourcemanagement/?cid=fsbdev3_046815). Fir includes Douglas fir-ponderosa pine, Douglas fir-white fir, mixed conifer-fir and red fir; pine includes eastside pine, Jeffrey pine and ponderosa pine; and oak includes canyon live oak and black oak.

[c]Classifications from the California Wildlife Habitat Relationships System [*Mayer and Laudenslayer*, 1988].

Table 3. Average (and standard deviation) of field plot attributes, organized by region and dominant tree species[a]

Region/ Dom. Type	Plots	Consumption (Mg ha^{-1})		BA (m^2 ha^{-1})		Density (ha^{-1})	
Klamath							
Fir	12	29	(27)	160	(170)	3000	(7600)
Oak	2	48	(9.4)	220	(240)	2100	(1200)
Pine	1	100		25		540	
Northern Sierra							
Fir	8	130	(140)	98	(120)	1100	(1500)
Oak	5	71	(61)	55	(53)	460	(360)
Pine	11	62	(38)	63	(39)	1100	(620)
Southern Sierra							
Fir	4	66	(89)	19	(5.5)	360	(320)
Juniper	1	82		15		600	
Pine	2	88	(110)	29	(14)	740	(710)

[a]Fir includes *Abies concolor* and *Pseudotsuga meziesii*; Oak includes *Quercus kelloggii* and *Q. chrysolepis*; Pine includes *Pinus lambertiana*, *P. jeffreyi* and *P. ponderosa*; Juniper includes *Juniperus occidentalis*.

Table 4. Average percent difference between modeled and observed consumption of total surface and ground fuels, with standard error (SE) and 95% confidence interval (CI)[a]

	% Diff	SE	Lower CI	Upper CI
Klamath				
S-high	780	630	-480	2000
S-typical	370	250	-140	880
S-low	110	100	-100	310
FCCS	48	85	-120	220
Sierra				
S-high	44	31	-18	110
S-typical	-18	13	-45	9.0
S-low	-62	5.7	-74	-51
FCCS	-28	12	-53	-3.3

[a]Positive values indicate over-prediction, and negative values indicate under-prediction.

Table 5. Emissions of concern to air quality[a]

	Flaming		Smoldering	
$PM_{2.5}$				
Field	85	(110)	970	(820)
S-high	54	(37)	3600	(2300)
S-typical	21	(9.5)	2100	(1300)
S-low	7.6	(3.6)	950	(600)
FCCS	44	(14)	990	(580)
PM_{10}				
Field	100	(130)	1100	(970)
S-high	63	(43)	4300	(2700)
S-typical	24	(11)	2400	(1500)
S-low	9.1	(4)	1100	(710)
FCCS	52	(16)	1200	(690)
CO				
Field	210	(280)	13000	(11000)
S-high	130	(91)	48000	(31000)
S-typical	51	(23)	28000	(17000)
S-low	19	(8.7)	13000	(8000)
FCCS	110	(34)	13000	(7800)
NO_x				
Field	100	(140)	0	(0)
S-high	66	(45)	0	(0)
S-typical	25	(12)	0	(0)
S-low	9.4	(4.3)	0	(0)
FCCS	54	(16)	0	(0)
SO_2				
Field	33	(43)	43	(36)
S-high	21	(14)	160	(100)
S-typical	7.8	(3.6)	92	(58)
S-low	2.8	(1.4)	42	(27)
FCCS	17	(5.1)	44	(26)

[a]Emission levels are in kg ha^{-1}, and show average (and standard deviation) of FOFEM predictions for field data and each model type.

Figure Legends

Figure 1. Map showing location of wildfires included in the study.

Figure 2. Pre- and post-fire fuel load of four fuel load components for field data and the four fuel model types (SAF/SRM low, typical and high, and FCCS). Data shown is for all plots with known spatial locations (n=46). Note breaks and scale changes in y-axis for shrubs and litter.

Figure 3. Conditional inference tree of difference in total ground and surface fuel consumption (Mg ha^{-1}) between each model and the corresponding plot data. Difference was calculated as the consumption predicted by a model minus the observed consumption for each plot. Positive values therefore indicate that models predicted more consumption than was observed in the field data, while negative values indicate less consumption predicted than observed. Total fuel load includes litter, duff, shrubs, herbaceous and all size classes of downed woody fuels.

Figure 4. Comparison of field data to models, showing averages of pre- and post-fire fuel load for each terminal node in the conditional inference tree presented in Figure 3.

Figure 5. GHG emissions predicted by FOFEM for the pre-fire field data and each model type. Error bars show the standard deviation for flaming and smoldering combined.

Figure 1.

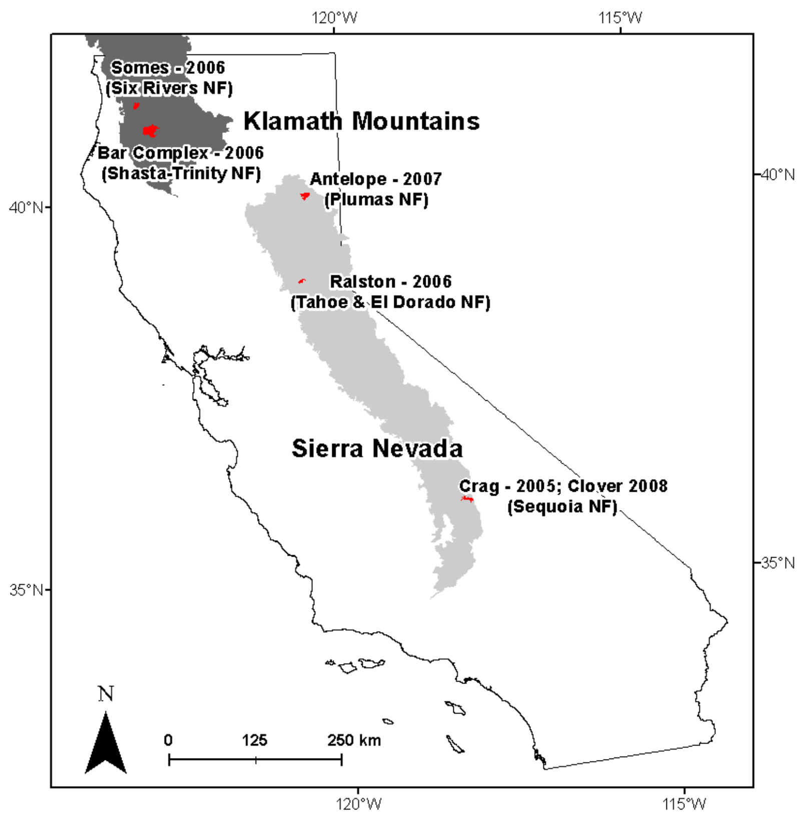

120°W
115°W
Somes - 2006
(Six Rivers NF)
Klamath Mountains
Bar Complex - 2006
(Shasta-Trinity NF)
Antelope - 2007
(Plumas NF)
40°N
40°N
Ralston - 2006
(Tahoe & El Dorado NF)
Sierra Nevada
Crag - 2005; Clover 2008
(Sequoia NF)
35°N
35°N
N
0
125
250 km
120°W
115°W

Figure 2.

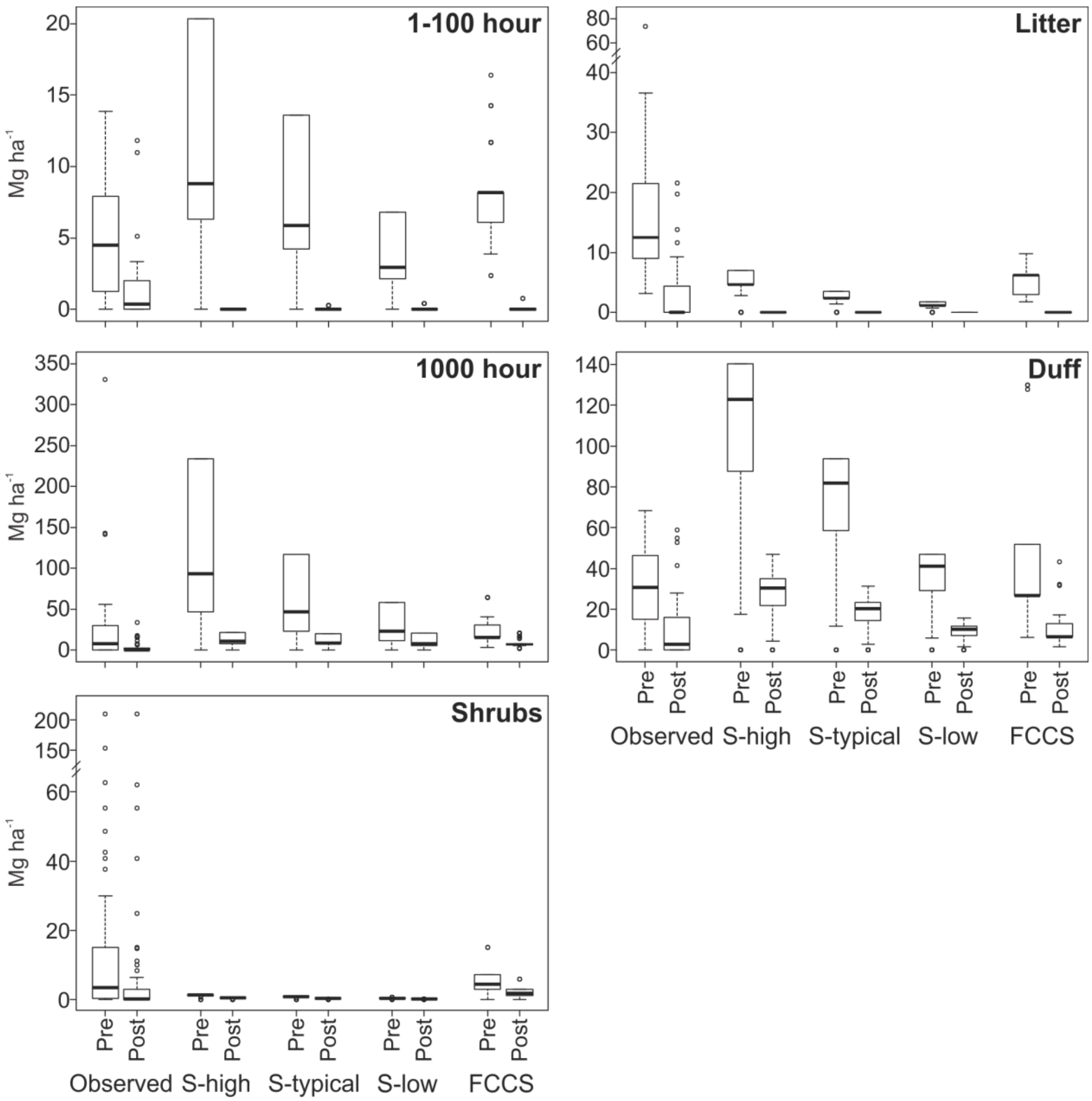
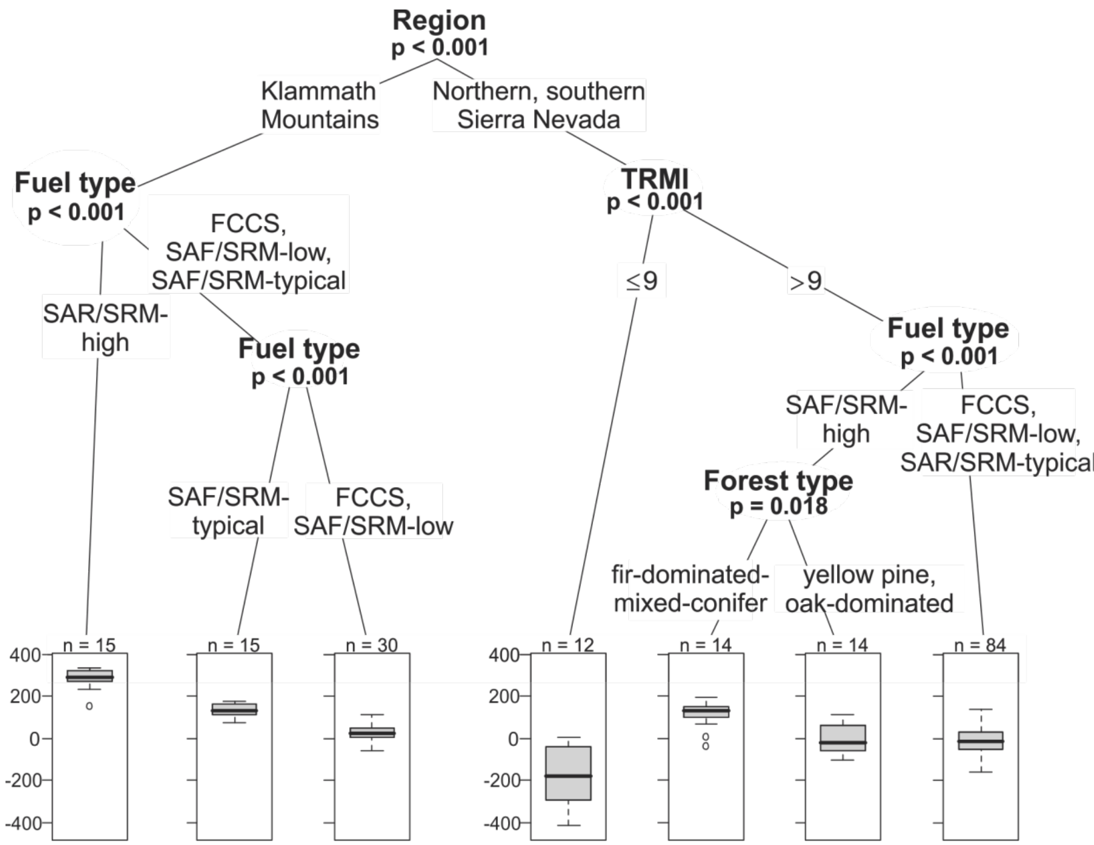
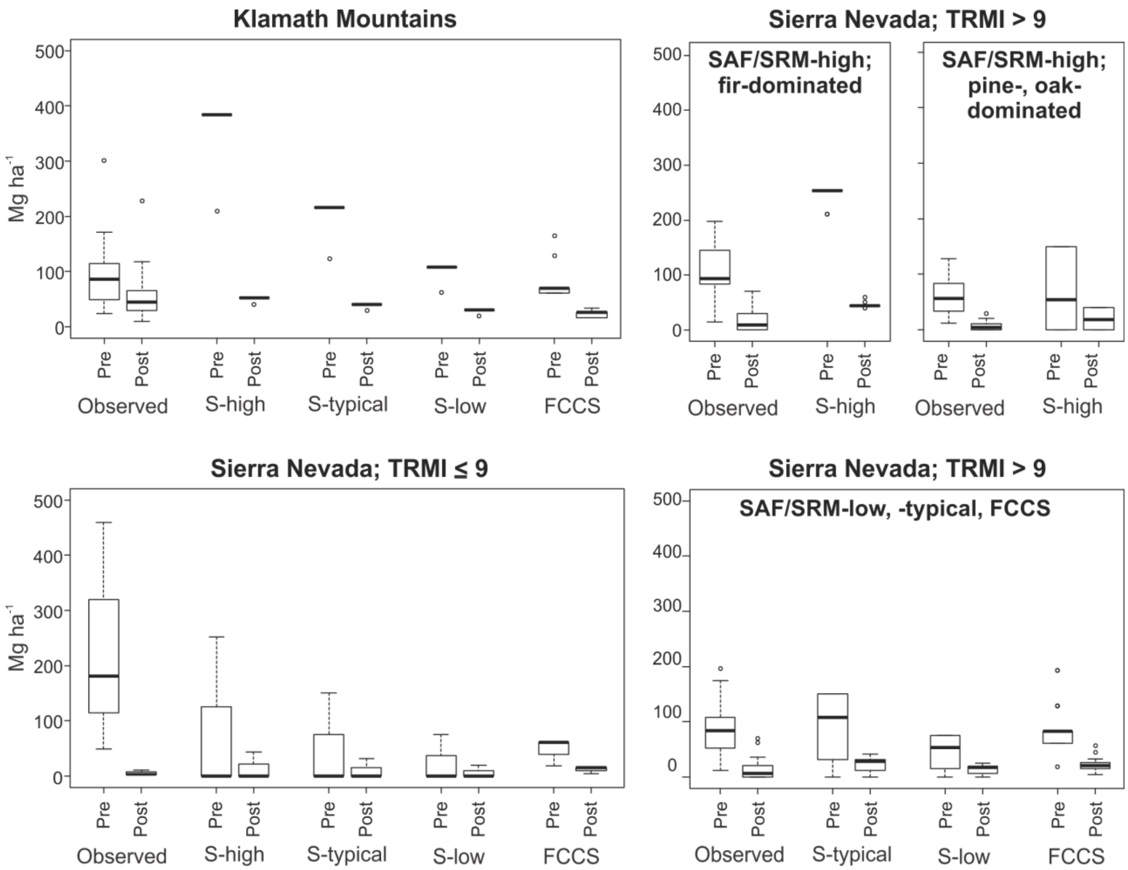

1-100 hour
Litter
1000 hour
Duff
Shrubs
Mg ha⁻¹
Pre
Post
Observed
S-high
S-typical
S-low
FCCS

Figure 3.



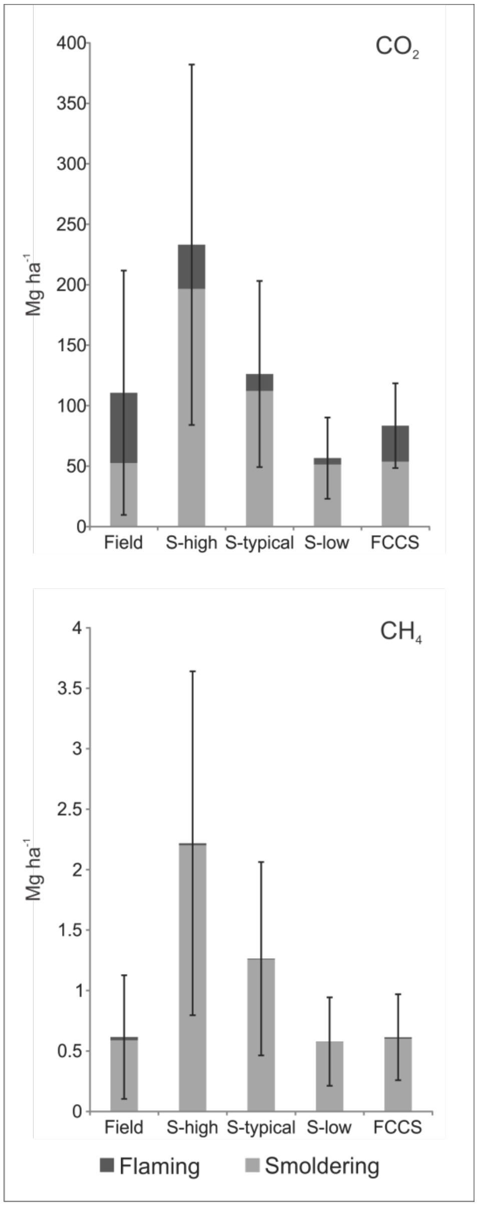
Region
p < 0.001
Klammath Mountains
Northern, southern Sierra Nevada
Fuel type
p < 0.001
FCCS, SAF/SRM-low, SAF/SRM-typical
SAR/SRM-high
Fuel type
p < 0.001
SAF/SRM-typical
FCCS, SAF/SRM-low
TRMI
p < 0.001
≤9
>9
Fuel type
p < 0.001
SAF/SRM-high
FCCS, SAF/SRM-low, SAR/SRM-typical
Forest type
p = 0.018
fir-dominated-mixed-conifer
yellow pine, oak-dominated
n = 15
n = 15
n = 30
n = 12
n = 14
n = 14
n = 84
400
200
0
-200
-400

Figure 4.



Klamath Mountains
Mg ha-1
500
400
300
200
100
0
Pre
Post
Observed
S-high
S-typical
S-low
FCCS
Sierra Nevada; TRMI > 9
SAF/SRM-high; fir-dominated
SAF/SRM-high; pine-, oak-dominated
Observed
S-high
Sierra Nevada; TRMI ≤ 9
Sierra Nevada; TRMI > 9
SAF/SRM-low, -typical, FCCS

Figure 5.



CO2
Mg ha-1
400
350
300
250
200
150
100
50
0
Field
S-high
S-typical
S-low
FCCS
CH4
4
3.5
3
2.5
2
1.5
1
0.5
Flaming
Smoldering

Appendix 2. Emissions from logging residues from California forests.

DRAFT REPORT

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EXECUTIVE SUMMARY

This report contributes to the project “California Forest and Rangeland Greenhouse Gas Inventory Development”, specifically Task 4 “For key land categories estimate statewide annual atmospheric CO2 removals and emissions of CO2, CH4, and N2O by process”. The objectives of our analysis included iii) GHG emissions from combustion and decomposition of forest harvest slash, and iv) GHG emissions from off-site combustion of forest harvest residues and non-agricultural biomass utilized for heat and power. We found that for a given year the CO2 emissions were about 8 to 9 million Mg although cumulatively over a 20 year period this increased to about 11 to 12 million Mg CO2 annual emissions due to decomposition.

1 INTRODUCTION AND OBJECTIVES

This report contributes to the project “California Forest and Rangeland Greenhouse Gas Inventory Development” (Proposal No. 20113281), Principal Investigator: John Battles. Task 4 of this project “For key land categories estimate statewide annual atmospheric CO2 removals and emissions of CO2, CH4, and N2O by process”.

The objectives of our analysis included iii) GHG emissions from combustion and decomposition of forest harvest slash, and iv) GHG emissions from off-site combustion of forest harvest residues and non-agricultural biomass utilized for heat and power.

2 METHODS AND DATA

2.1 CA-residues from wood products profile

2.1.1 CA forest harvest

We estimated the residue produced for commercial and non-commercial operations in California for the year 2006. This year was selected due to the availability of data provided by the research of the USDA Forest Service Forest Inventory Analysis program (Morgan, Songster et al. 2012). The emissions and storage from 2006 to the year 2025 was estimated. In order to provide data to the larger analysis, which examined stock changes from 2001 to 2008, we also produced estimates for those years.

We used harvest data from the 2010 FRAP Assessment (FRAP 2010) and the US Forest Service (USFS FACS Export 2010) to determine clearcut and partial harvest acres in California for 2001, 2006 and 2008. We assumed that 33 percent of volume was removed in partial cuts on average. In total, 109.3 million cubic feet (MMCF) of residuals was produced in 2006 (Todd Morgan, personal communication). This was converted to carbon using the conversion factor of 15.11 lb C per cubic foot for Pacific Southwest softwoods (Skog and Nicholson 2000). The proportion allocated to partial harvest and clearcut was pro-rated based on relative proportions of the prescriptions for private and Forest Service lands in 2006.

2.1.2 Emissions and storage pools

Table 1 shows the assumed logging residue disposition by treatment and silvicultural class. We assumed 1 bone-dry ton extracted for each thousand board feet (MBF) harvested (personal communication, Tad Mason TSS consultants). For non-commercial harvests, we assumed the same extraction rate for slash associated with the lumber section of commercial harvests, plus collecting 20% of remaining slash. We also assumed 95 percent of partial harvests and clearcuts had residues scattered intentionally post-processing at landing site (Stewart and Nakamura 2012).

Table 1. Logging residue disposition.

Logging Residue Treatments	Clearcut	Commercial Partial Cuts	Non-commercial Partial Cuts Including Fuel Reduction
Extracted	89.3%	89.3%	29.1%
Pile Burned	5.0%	5.0%	30.0%
Decay On Site	5.7%	5.7%	40.9%

The total CO_2 emissions were the sum of the bioenergy (extracted), pile burned, and decayed on site.

The extracted residues for biomass energy for the year of combustion was calculated as the sum of the bole (Morgan, Songster et al. 2012), logging residues and bark with the ash (Wiinikka, Grönberg et al. 2013) and CH_4 emissions reported separately. The wood processing loss from residues was also added in, with CH_4 emissions reported separately. The subsequent year's emissions were calculated with an annual decay rate of 2.3 percent of the remaining un-combusted carbon (Turner, Koerper et al. 1995).

The pile burned emissions for a given year was calculated as the sum of the weighted amounts of the clearcut and partial cut emissions (based on Table 1), with the emissions as the form of CH_4 (3.5 percent) (IPCC 2006) and CO (7.7 percent) (FRAP 2010) reported separately. The first year emissions for pile burning was 93 percent (Finkral, Evans et al. 2012). The annual decomposition rate for the carbon remaining after the first year was 3.5 percent (DeLuca and Aplet 2008).

The decay-on-site portion was estimated by multiplying the sum of the commercial and non-commercial residues by the decay rates for clearcut and partial cuts; and then subtracting off the methane. This is decayed (emitted) at the annual emission rate of 2.3 percent from Turner et al. (1995).

3 RESULTS AND DISCUSSION

Tables 2 to 4 show the results of the emissions of CO_2 for the three categories of bioenergy, scattered (left on site), and pile burned for the years 2001, 2006, and 2008 respectively. The results are shown for the initial year of 2001, 2006 and 2008; and annually to 2020, 2025 and 2027 respectively. The results are shown graphically in Figures 1 to 3. Annual emissions and cumulative emissions are shown. The cumulative CO_2 emissions in the year 2025 (for the 2006 harvests) were 7.6 Million Mg from bioenergy, 3.4 Mg from left on site, and 0.3 Mg from pile burned. These were slightly lower for 2001 and higher for 2008 but within about 1 Mg.

The estimated emission from CH4 were totals over the 20-year period of 138,171, 178,826 and 143,961 Mg with most from material left on site. The estimated emissions from CO were for the piled burned only in the first year only and were 10,657, 17,146, and 25,163 Mg in 2001, 2006 and 2008 respectively.

As Figures 1 to 3 show, bioenergy emissions was the largest source of emissions for harvest residues in California for all the years. Emissions are primarily at the time of combustion, which is also true for pile burning. The residue left on site (scattered) decays over time and ends up as the second largest emission category. There are a number of assumptions necessary for this analysis. The harvest levels, harvest methods, slash disposal methods, and availability of biomass energy processing facilities will all have an effect on the estimates for a given year.

Table 2. CO2 emissions from residue categories for harvests in 2001.

Year	Total (20yr)	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
CO2 emissions	**10,825,103**	**7,740,818**	**355,394**	**319,971**	**288,088**	**259,390**	**233,560**	**210,310**	**189,383**	**170,546**	**153,591**	**138,329**	**124,590**	**112,224**	**101,092**	**91,071**	**82,050**	**73,929**	**66,619**	**60,037**	**54,112**
Bioenergy	**7,345,270**	7,321,747	1,514	1,479	1,445	1,412	1,380	1,348	1,317	1,287	1,257	1,228	1,200	1,172	1,145	1,119	1,093	1,068	1,043	1,019	996
Scattered	**3,292,932**	232,180	353,879	318,491	286,642	257,978	232,180	208,962	188,066	169,259	152,333	137,100	123,390	111,051	99,946	89,951	80,956	72,861	65,574	59,017	53,115
Pile burnt	**186,902**	186,891	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54

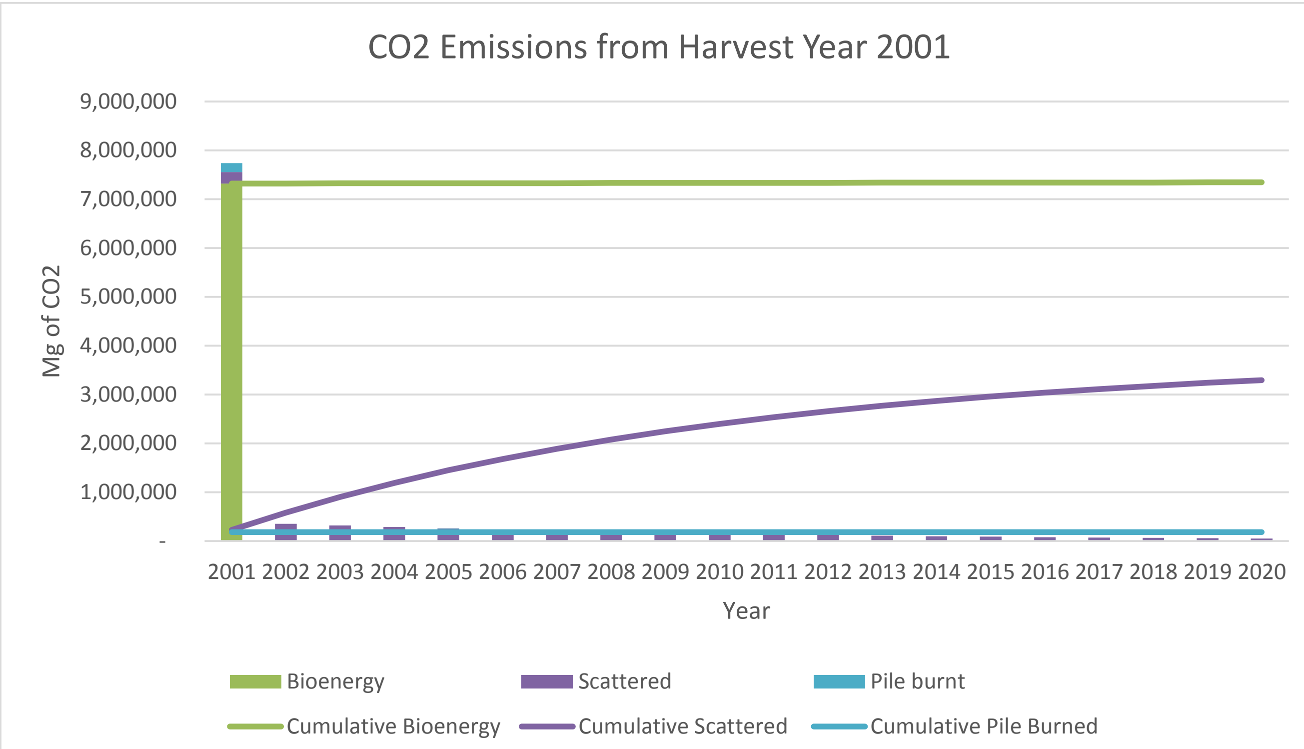

Figure 1. Annual (stacked bars) and cumulative (lines) CO2 emissions from harvests in 2001.

Table 3. CO2 emissions from residue categories for harvests in 2006.

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
CO2 emissions	**8,291,898**	**352,205**	**317,113**	**285,527**	**257,097**	**231,508**	**208,474**	**187,741**	**169,079**	**152,281**	**137,159**	**123,548**	**111,295**	**100,265**	**90,336**	**81,398**	**73,351**	**66,106**	**59,585**	**53,713**
Bioenergy	7,601,733	1,670	1,632	1,594	1,558	1,522	1,487	1,453	1,419	1,387	1,355	1,324	1,293	1,263	1,234	1,206	1,178	1,151	1,125	1,099
Scattered	389,482	350,533	315,480	283,932	255,539	229,985	206,986	186,288	167,659	150,893	135,804	122,223	110,001	99,001	89,101	80,191	72,172	64,955	58,459	52,613
Pile burned	300,683	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86

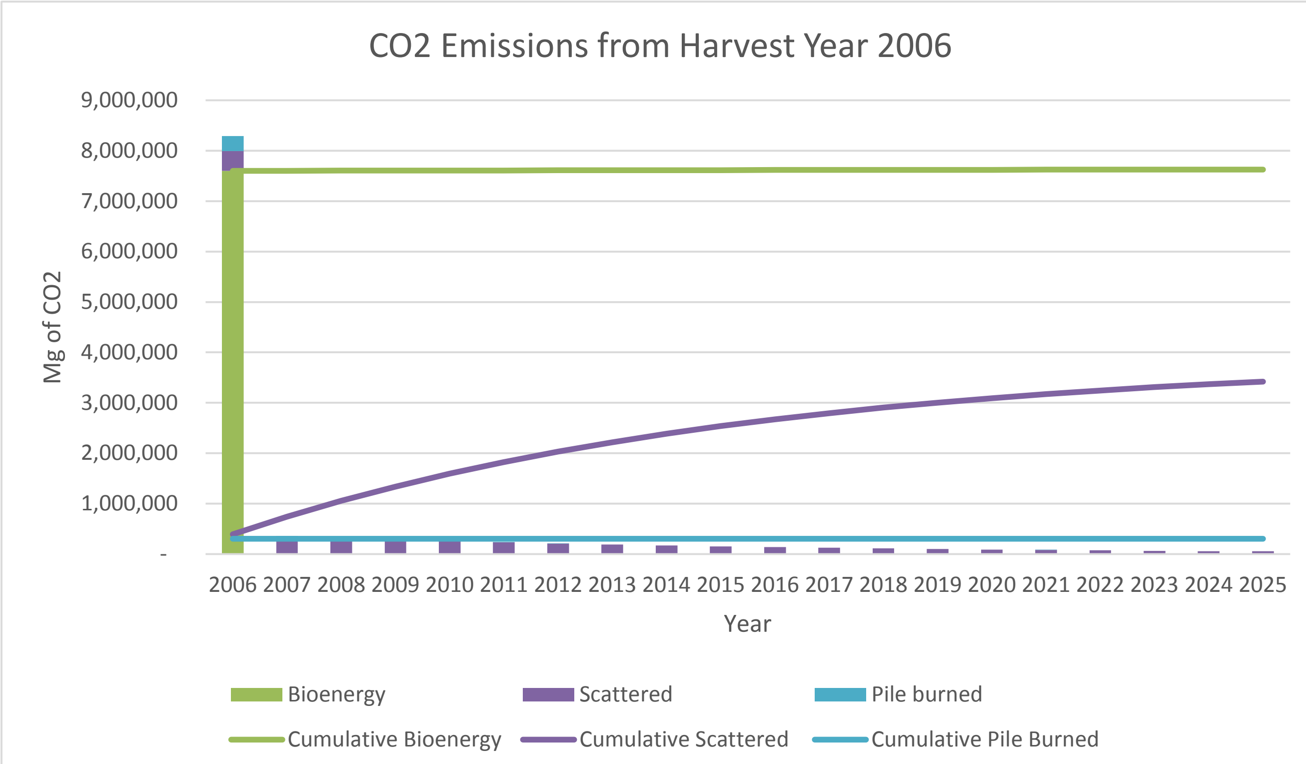

Figure 2. Annual (stacked bars) and cumulative (lines) CO2 emissions from harvests in 2006.

Table 4. CO2 emissions from residue categories for harvests in 2008.

Year	**Total (20yr)**	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
CO2 emissions	**12,622,770**	**8,908,371**	**427,997**	**385,338**	**346,942**	**312,382**	**281,275**	**253,276**	**228,073**	**205,389**	**184,969**	**166,589**	**150,045**	**135,152**	**121,746**	**109,678**	**98,814**	**89,034**	**80,230**	**72,304**	**65,169**
Bioenergy	**7,910,879**	7,882,498	1,827	1,785	1,744	1,704	1,664	1,626	1,589	1,552	1,517	1,482	1,448	1,414	1,382	1,350	1,319	1,289	1,259	1,230	1,202
Scattered	**4,270,588**	584,593	426,168	383,552	345,196	310,677	279,609	251,648	226,483	203,835	183,452	165,106	148,596	133,736	120,363	108,326	97,494	87,744	78,970	71,073	63,966
Pile burnt	**441,304**	441,280	1.27	1.27	1.27	1.27	1.27	1.27	1.27	1.27	1.27	1.27	1.27	1.27	1.27	1.27	1.27	1.27	1.27	1.27	1.27

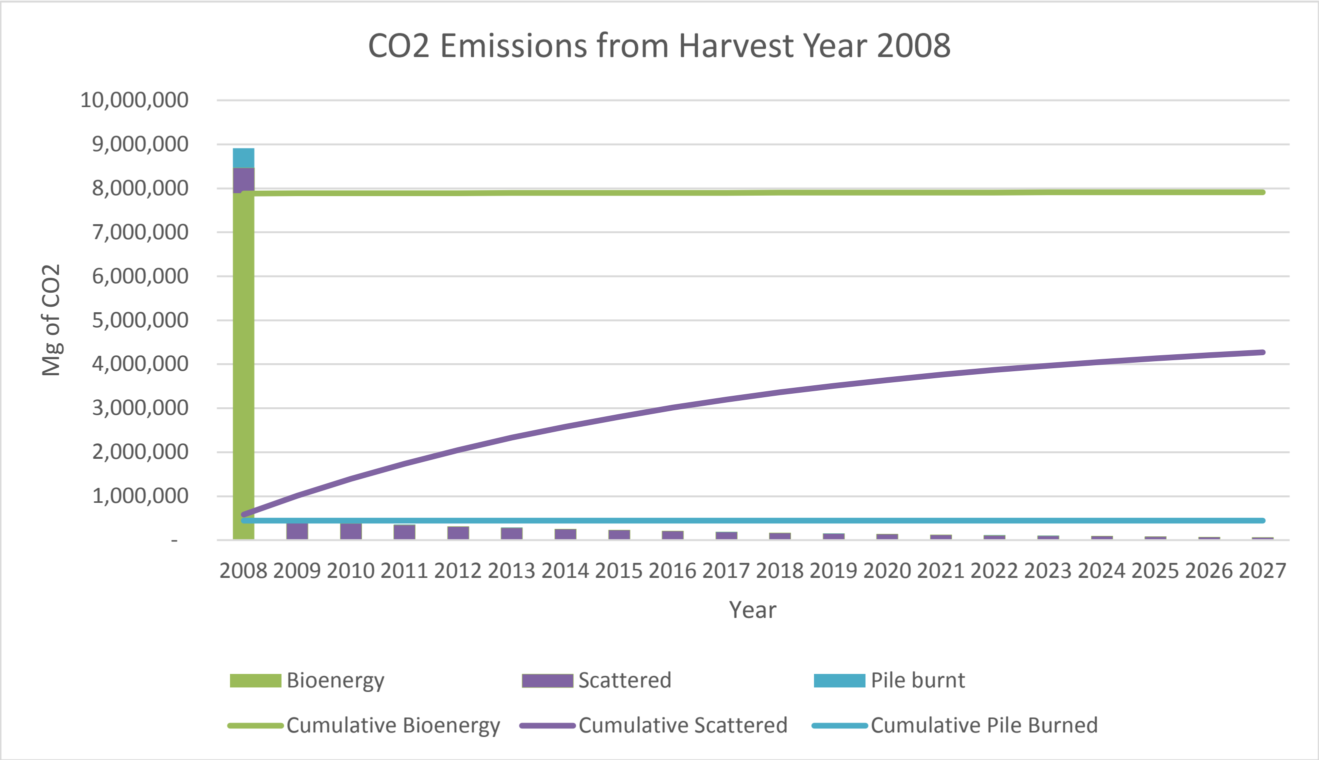

Figure 3. Annual (stacked bars) and cumulative (lines) CO2 emissions from harvests in 2008

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Appendix 3. Carbon Dioxide (CO_2) Emissions Estimates Associated with Silviculture Applications for California Forests

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September 8, 2013

1 Introduction and Purpose

Harvesting of timber results in emissions of CO_2 as the carbon in the trees goes through the decomposition processes. Whether the forest sector as a whole contributes to overall increases of CO_2 in the atmosphere depends on the rate of decomposition of the timber harvested (some of the harvested material goes into long-term wood products where it remains sequestered, for example) and the rate of forest growth whereby CO_2 is removed from the atmosphere and stored in trees and other forest carbon pools (IPCC 2006, Canadell and Raupach 2008).

The purpose of this analysis is to provide estimates of CO_2 emissions associated with common silviculture applications on the combinations of forest types and development stages in California. The estimates will be used as an accounting tool to track the trends of forest carbon in California. The tool provides estimates of metric tons (tonnes) of CO_2 on a per-acre basis by forest community, forest condition, and silviculture application. Overall estimates of immediate emissions are determined by multiplying the per-acre values by the actual acres of silviculture applied to the appropriate forest community and condition.

2 Analytical Steps

The following steps were involved in the analysis and are described in greater detail below:

- Allocation of FIA (FIA 2010) plot data to forest vegetation strata based on classes of forest communities, forest canopy cover, and forest height.
- Summarizing tree data for each forest community to generate estimates of average basal area (sq. ft. per acre) and average carbon dioxide (tonnes CO_2 per acre).
- Calculating a ratio of CO_2 /basal area for each forest vegetation stratum.
- Establishing retention levels for dominate silviculture activities occurring within the state.
- Deriving estimates of CO_2 emissions associated with silviculture activities based on applying CO_2 to basal area ratios to the surplus basal area above retention levels for each stratum.

Note that the US customary units of acres and square feet of basal area were used for this analysis to correspond with California Forest Practice Act and associated regulations.

3 Input Data

The data used in developing these estimates is based on Landfire (LANDFIRE 2013) and USFS Forest Inventory and Analysis (FIA) inventory plots (FIA 2010). The Landfire data is based on 30-meter pixels. The extent of the unprocessed dataset includes all pixels that have some form of forest cover. This dataset was further refined to only include those pixels that are associated with commercial timber species. Table 1 displays the variables and classes related to forest communities, where harvesting occurs. These were attributed to each FIA plot located in Landfire pixels identified as 'Tree-Dominated'.

Table 1. Landfire classes for cover, height and community.

Data Label	A unique identifier and common element with 'Plot' in the related tree dataset.	
EVC	Forest Canopy Cover	Tree Cover in 10% canopy closure classes, including: • >=10% < 20% • >=20% < 30% • >=30% < 40% • >=40% < 50% • >=50% < 60% • >=60% < 70% • >=70% < 80% • >= 80% < 90% • >= 90% < 100%
EVH	Forest Height	Forest height defined in the following classes: • 0-5 meters • 5-10 meters • 10 – 25 meters • 25 – 50 meters • > 50 meters
EVT	Forest Community	A class made up of forest communities in California, including communities that provide commercial timber and those that do not. Forest communities were extracted from the original dataset if commercial timber harvesting occurs within the community. The communities included were: • California Coastal Redwood Forest • California Montane Jeffrey Pine(-Ponderosa Pine) Woodland • East Cascades Oak-Ponderosa Pine Forest and Woodland • Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland • Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland • Mediterranean California Mesic Mixed Conifer Forest and Woodland • Mediterranean California Mixed Evergreen Forest • Mediterranean California Red Fir Forest • Northern Rocky Mountain Ponderosa Pine Woodland and Savanna • Sierra Nevada Subalpine Lodgepole Pine Forest and Woodland

Each plot from within the included forest communities had related tree data. The tree data included all trees associated with the plot and detail related to species, diameter at breast height (dbh (in.), 4.5 feet high on tree), total height (ft.), carbon (tonnes CO_2), and number of trees per acre the tree record represented in the sample.

4 Forest Vegetation Strata

The data associated with forest communities where commercial timber harvest occurs was placed into broader classes with an intent to mimic the dominate classes of forest conditions found in California and to facilitate the use of the tool.

4.1 Forest Community Classes

The full suite of forest communities where harvesting might occur were included as the initial data set. The number of plots associated with each forest community was reviewed. The East Cascades Oak-Ponderosa Pine Forest and Woodland had very few (6) plots associated with it and the estimates derived from this data would not be robust. The community was merged with the Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland for this analysis.

4.2 Forest Canopy Cover Classes

Each plot was attributed with a canopy closure class in 10% categories. These classes were merged to generate broader canopy cover classes that generally represent conditions in forest management stages (recently harvested, growing, and mature). Table 2 displays the placement of the raw data into broad canopy cover classes. The decision on where to establish the classes also took into consideration plots that appeared to be part of primary forests. Such forests are not likely to be part of a harvest event and influence plot data summaries due to their extremely high levels of basal area (sq. ft. per acre) and CO_2e content (tonnes per acre).

Table 2. Forest Canopy Cover Classes.

EVC (Raw Input Data)	Assigned Canopy Closure Class
Tree Cover >= 10 and < 20%	Open
Tree Cover >= 20 and < 30%	Open
Tree Cover >= 30 and < 40%	Medium
Tree Cover >= 40 and < 50%	Medium
Tree Cover >= 50 and < 60%	Medium
Tree Cover >= 60 and < 70%	Dense
Tree Cover >= 70 and < 80%	Dense
Tree Cover >= 80 and < 90%	Closed
Tree Cover >= 90 and <= 100%	Closed

4.3 Forest Height Classes

Each plot was allocated a height class. As with canopy closure data, the forest height data was merged into broad classes consistent with field conditions associated with forest management events (recently harvested, growing, and mature). As with Forest Canopy Closure classes, the decision on where to establish the classes also took into consideration plots that appeared to be part of primary forests. Such forests are not likely to be part of a harvest event and influence plot data summaries due to their extremely high levels of basal area and CO_2e content. The crosswalk between raw input data and the forest height classes used in the analysis is shown in Table 3.

Table 3. Forest Height Classes.

EVH (Raw Input Data)	Assigned Height Class
Forest Height 0 to 5 meters	Small
Forest Height 5 to 10 meters	Small
Forest Height 10 to 25 meters	Medium
Forest Height 25 to 50 meters	Large
Forest Height > 50 meters	Extra Large

The combinations of Forest Community, Forest Canopy Closure, and Forest Height resulted in 65 combinations of forest strata. Plot counts were reviewed to determine if an adequate number of plots remained with each defined forest vegetation stratum. A review of the forest vegetation strata that had fewer plots was determined to be of little concern since the strata represent forest conditions that are generally not subject to harvesting events. That is, strata with few plots were generally in what were apparent reserves or associated with very young forest conditions. Table 4 displays the number of strata derived from the combinations of Forest Community, Forest Canopy Closure, and Forest Height.

Table 4. Forest Vegetation Strata and Associated Plot Count.

Forest Vegetation Strata	Height Class	Closure Class	Plot Count
California Coastal Redwood Forest	ExtraLarge	Dense	2
	ExtraLarge	Medium	3
	Large	Closed	6
	Large	Dense	84
	Large	Medium	21
	Medium	Closed	8
	Medium	Dense	48
	Medium	Medium	11
	Small	Medium	1
California Montane Jeffrey Pine(-Ponderosa Pine) Woodland	Large	Dense	3
	Large	Medium	34
	Medium	Dense	23
	Medium	Medium	175
	Medium	Open	35
	Small	Medium	18
	Small	Open	10
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland	Large	Closed	5
	Large	Dense	220
	Large	Medium	77
	Medium	Dense	63
	Medium	Medium	108

Forest Vegetation Strata	Height Class	Closure Class	Plot Count
	Medium	Open	9
	Small	Medium	27
	Small	Open	4
Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland	Large	Closed	1
	Large	Dense	10
	Large	Medium	4
	Medium	Closed	1
	Medium	Dense	37
	Medium	Medium	37
	Medium	Open	2
	Small	Dense	2
	Small	Open	3
Mediterranean California Mesic Mixed Conifer Forest and Woodland	ExtraLarge	Dense	1
	ExtraLarge	Medium	4
	Large	Closed	5
	Large	Dense	251
	Large	Medium	277
	Large	Open	1
	Medium	Dense	44
	Medium	Medium	164
	Medium	Open	15
	Small	Medium	4
Mediterranean California Mixed Evergreen Forest	ExtraLarge	Dense	1
	Large	Closed	27
	Large	Dense	102
	Large	Medium	15
	Medium	Closed	11
	Medium	Dense	58
	Medium	Medium	8
	Medium	Open	1
	Small	Medium	1
Mediterranean California Red Fir Forest	Large	Dense	24
	Large	Medium	218
	Large	Open	7
	Medium	Medium	73
	Medium	Open	25
	Large	Medium	10

Forest Vegetation Strata	Height Class	Closure Class	Plot Count
Northern Rocky Mountain Ponderosa Pine Woodland and Savanna	Large	Open	1
	Medium	Medium	57
	Medium	Open	44
	Small	Open	2
Sierra Nevada Subalpine Lodgepole Pine Forest and Woodland	Large	Medium	4
	Medium	Medium	32
	Medium	Open	8

5 Summary Calculations

Average estimates of basal area (sq. ft. per acre) and CO_2e content (tonnes per acre) were calculated for each forest stratum. The estimate of CO_2e was divided by the estimate of basal area to calculate a ratio that was applied to stocking levels to calculate the emission associated with the removal of each unit of basal area.

Table 5. Carbon to basal area ratios by forest categories.

Forest Communities	Canopy Closure Class	Height Class	Average Basal Area (sq. ft. /acre)	Average CO_2e (tonnes per acre)	CO_2e/BA Ratio (tonnes/sq. ft.)
California Coastal Redwood Forest	Closed	Large	411	731	1.78
	Closed	Medium	196	192	0.98
	Dense	Extra Large	609	1,060	1.74
	Dense	Large	251	306	1.22
	Dense	Medium	169	148	0.87
	Medium	Extra Large	372	577	1.55
	Medium	Large	165	186	1.13
	Medium	Medium	78	70	0.89
	Medium	Small	94	79	0.84
California Montane Jeffrey Pine(-Ponderosa Pine) Woodland	Dense	Large	287	292	1.02
	Dense	Medium	243	201	0.83
	Medium	Large	162	136	0.84
	Medium	Medium	127	91	0.71
	Medium	Small	70	44	0.63
	Open	Medium	54	34	0.63
	Open	Small	44	22	0.51

Forest Communities	Canopy Closure Class	Height Class	Average Basal Area (sq. ft. /acre)	Average CO_2e (tonnes per acre)	CO_2e/BA Ratio (tonnes/sq. ft.)
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland	Closed	Large	248	369	1.49
	Dense	Large	213	271	1.27
	Dense	Medium	135	130	0.96
	Medium	Large	197	208	1.05
	Medium	Medium	91	80	0.88
	Medium	Small	61	58	0.95
	Open	Medium	57	29	0.51
	Open	Small	70	77	1.09
Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland	Closed	Large	256	440	1.72
	Closed	Medium	154	167	1.08
	Dense	Large	203	286	1.41
	Dense	Medium	111	117	1.05
	Dense	Small	99	132	1.33
	Medium	Large	183	211	1.15
	Medium	Medium	113	107	0.95
	Open	Medium	50	32	0.63
	Open	Small	40	36	0.92
Mediterranean California Mesic Mixed Conifer Forest and Woodland	Closed	Large	165	227	1.38
	Dense	Extra Large	213	372	1.75
	Dense	Large	267	314	1.18
	Dense	Medium	144	100	0.70
	Medium	Extra Large	561	528	0.94
	Medium	Large	214	221	1.03
	Medium	Medium	119	89	0.75
	Medium	Small	117	85	0.72
	Open	Large	171	73	0.43
	Open	Medium	49	31	0.64
Mediterranean California Mixed Evergreen Forest	Closed	Large	253	318	1.26
	Closed	Medium	189	194	1.03
	Dense	Extra Large	406	667	1.64

Forest Communities	Canopy Closure Class	Height Class	Average Basal Area (sq. ft. /acre)	Average CO_2e (tonnes per acre)	CO_2e/BA Ratio (tonnes/sq. ft.)
	Dense	Large	272	371	1.36
	Dense	Medium	158	159	1.01
	Medium	Large	114	140	1.23
	Medium	Medium	69	58	0.84
	Medium	Small	55	42	0.76
	Open	Medium	30	17	0.56
	Dense	Large	374	390	1.04
	Medium	Large	228	220	0.97
	Medium	Medium	136	93	0.69
	Open	Large	138	127	0.92
	Open	Medium	119	81	0.68
Northern Rocky Mountain Ponderosa Pine Woodland and Savanna	Medium	Large	113	98	0.87
	Medium	Medium	95	58	0.61
	Open	Large	34	26	0.76
	Open	Medium	49	28	0.58
	Open	Small	25	25	0.99
Sierra Nevada Subalpine Lodgepole Pine Forest and Woodland	Medium	Large	220	212	0.96
	Medium	Medium	222	165	0.74
	Open	Medium	126	71	0.56

6 Silviculture

The silviculture applications are based on dominant activities included within the California Forest Practice Rules (FPRs) (CALFIRE 2012). The California Forest Practice Act and associated regulations apply to private and state timberlands excluding State Parks and all federal lands. The retention levels used are based on retention levels required for each silviculture type described in the FPRs applied to Group A and Group B species in the FPRs. Group A species are generally commercial species like redwood, Douglas-fir, ponderosa pine, white and red fir, while Group B species are generally non-commercial species including most hardwoods. Since the data included in the inventory include Group A, Group B, and species that are not found in either list, additional basal area retention was applied to each silviculture type above the FPRs to reflect retention of non-commercial tree species within harvest units. This is because it is customary to manage FPR retention levels based only on Group A species. Group B species are often reduced in stocking but are not eradicated.

No attempt was made to specify retention levels for varying site classes, as occurs in the FPRs, since the input data was not provided at that level of resolution and the tool is intended to provide a generalized and standardized estimate of emissions. The silvicultural types with the associated retention levels are shown in Table 5. While retention level specified by the regulations vary by region, those constraints were met using the higher retention levels we modeled due to the fact that harvests often do not cut to the rule minimums.

Table 5. Silviculture Methods and Associated Basal Area Retention Used.

Silviculture Name	Total Basal Area Retention (sq. ft. per acre)
Clearcut	10
Seed Tree Removal	10
Seed Tree Seed Step	30
Shelterwood Removal	10
Shelterwood Seed Step	60
Commercial Thinning	140
Selection	125
Variable Retention	45

7 Emissions Estimates

Estimates of forest emissions from harvest (CO_2) were derived by subtracting the basal area retention from the current estimates of basal area from the FIA inventory and then multiplying the difference by the CO_2 to basal area ratio for each forest vegetation stratum and for each silviculture method identified. Estimates of the amount of CO_2 stored in long-term wood products are based on the following assumptions:

1. All of the harvest in California is destined for sawtimber, which was estimated (Morgan, Songster et al. 2012) to be 88 percent of wood products produced in California (10 percent was panels). Sawtimber remains out of the atmosphere for long periods of time. Pulp, paper and other similar products do not.
2. Approximately 60% of the carbon in harvested trees is found in the bole portion of the tree that is delivered to the mill (FIA 2010).
3. Mills are approximately 68% efficient (DOE 2007). That is, 68% of the carbon entering the mill leaves the mill as a long term product.
4. Approximately 40% of the sawtimber produced remains out of the atmosphere for a substantial timeframe (DOE 2007).

Therefore, the formula used to estimate CO_2 stored in long-term wood products was as follows:

$CO_{2\text{ (harvested wood products)}} = CO_{2\text{(whole tree harvested)}} * 60\%_{\text{ (bole portion of tree)}} * 68\%_{\text{ (mill efficiency)}} * 40\%_{\text{ (portion held out of atmosphere for substantial time)}}$

Table 6 displays the emissions estimates (metric tons CO2 per acre) associated with each silvicultural method applied to each stratum. Some of the silviculture applications may appear unlikely (a clearcut applied to a small, open forest for example), however no effort was made to edit the list for likely silvicultural events. The estimates are provided for such rare harvest events.

Table 6. Emission estimates by forest vegetation class and silvicultural type.

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
California Coastal Redwood Forest	Closed	Large	Clearcut	713	116	597
			Commercial Thinning	482	79	403
			Seed Tree Removal	713	116	597
			Seed Tree Seed Step	677	111	567
			Selection	508	83	425
			Shelterwood Removal	713	116	597
			Shelterwood Seed Step	624	102	522
			Variable Retention	651	106	545
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Coastal Redwood Forest	Closed	Medium	Clearcut	182	30	152
			Commercial Thinning	55	9	46
			Seed Tree Removal	182	30	152
			Seed Tree Seed Step	162	27	136
			Selection	70	11	58
			Shelterwood Removal	182	30	152
			Shelterwood Seed Step	133	22	111
			Variable Retention	148	24	124
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**

California Coastal Redwood Forest	Dense	ExtraLarge	Clearcut	1,043	170	873
			Commercial Thinning	817	133	683
			Seed Tree Removal	1,043	170	873
			Seed Tree Seed Step	1,008	165	843
			Selection	843	138	705
			Shelterwood Removal	1,043	170	873
			Shelterwood Seed Step	956	156	800
			Variable Retention	982	160	822
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Coastal Redwood Forest	Dense	Large	Clearcut	294	48	246
			Commercial Thinning	136	22	114
			Seed Tree Removal	294	48	246
			Seed Tree Seed Step	270	44	226
			Selection	154	25	129
			Shelterwood Removal	294	48	246
			Shelterwood Seed Step	233	38	195
			Variable Retention	252	41	210
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Coastal Redwood Forest	Dense	Medium	Clearcut	139	23	116
			Commercial Thinning	25	4	21
			Seed Tree Removal	139	23	116
			Seed Tree Seed Step	121	20	101
			Selection	38	6	32

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
			Shelterwood Removal	139	23	116
			Shelterwood Seed Step	95	16	80
			Variable Retention	108	18	91
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Coastal Redwood Forest	Medium	ExtraLarge	Clearcut	562	92	470
			Commercial Thinning	360	59	301
			Seed Tree Removal	562	92	470
			Seed Tree Seed Step	531	87	444
			Selection	383	63	321
			Shelterwood Removal	562	92	470
			Shelterwood Seed Step	484	79	405
			Variable Retention	507	83	425
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Coastal Redwood Forest	Medium	Large	Clearcut	175	29	146
			Commercial Thinning	28	5	23
			Seed Tree Removal	175	29	146
			Seed Tree Seed Step	152	25	127
			Selection	45	7	38
			Shelterwood Removal	175	29	146
			Shelterwood Seed Step	118	19	99
			Variable Retention	135	22	113
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Coastal	Medium	Medium	Clearcut	61	10	51

Redwood Forest			Commercial Thinning	70	11	58
			Seed Tree Removal	61	10	51
			Seed Tree Seed Step	43	7	36
			Selection	70	11	58
			Shelterwood Removal	61	10	51
			Shelterwood Seed Step	16	3	13
			Variable Retention	29	5	25
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Coastal Redwood Forest	Medium	Small	Clearcut	71	12	59
			Commercial Thinning	79	13	66
			Seed Tree Removal	71	12	59
			Seed Tree Seed Step	54	9	45
			Selection	79	13	66
			Shelterwood Removal	71	12	59
			Shelterwood Seed Step	28	5	24
			Variable Retention	41	7	34
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Montane Jeffrey Pine(-Ponderosa Pine) Woodland	Dense	Large	Clearcut	282	46	236
			Commercial Thinning	150	24	125
			Seed Tree Removal	282	46	236
			Seed Tree Seed Step	262	43	219
			Selection	165	27	138
			Shelterwood Removal	282	46	236

			Shelterwood Seed Step	231	38	194
			Variable Retention	247	40	206
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Montane Jeffrey Pine(-Ponderosa Pine) Woodland	Dense	Medium	Clearcut	192	31	161
			Commercial Thinning	85	14	71
			Seed Tree Removal	192	31	161
			Seed Tree Seed Step	176	29	147
			Selection	97	16	82
			Shelterwood Removal	192	31	161
			Shelterwood Seed Step	151	25	126
			Variable Retention	164	27	137
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Montane Jeffrey Pine(-Ponderosa Pine) Woodland	Medium	Large	Clearcut	128	21	107
			Commercial Thinning	19	3	16
			Seed Tree Removal	128	21	107
			Seed Tree Seed Step	111	18	93
			Selection	31	5	26
			Shelterwood Removal	128	21	107
			Shelterwood Seed Step	86	14	72
			Variable Retention	99	16	83
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Montane Jeffrey Pine(-Ponderosa	Medium	Medium	Clearcut	83	14	70
			Commercial Thinning	91	15	76

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
Pine) Woodland			Seed Tree Removal	83	14	70
			Seed Tree Seed Step	69	11	58
			Selection	1	-	1
			Shelterwood Removal	83	14	70
			Shelterwood Seed Step	48	8	40
			Variable Retention	58	10	49
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Montane Jeffrey Pine(-Ponderosa Pine) Woodland	Medium	Small	Clearcut	38	6	32
			Commercial Thinning	44	7	37
			Seed Tree Removal	38	6	32
			Seed Tree Seed Step	25	4	21
			Selection	44	7	37
			Shelterwood Removal	38	6	32
			Shelterwood Seed Step	6	1	5
			Variable Retention	16	3	13
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Montane Jeffrey Pine(-Ponderosa Pine) Woodland	Open	Medium	Clearcut	28	5	23
			Commercial Thinning	34	6	29
			Seed Tree Removal	28	5	23
			Seed Tree Seed Step	15	2	13
			Selection	34	6	29
			Shelterwood Removal	28	5	23
			Shelterwood Seed Step	34	6	29

			Variable Retention	6	1	5
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
California Montane Jeffrey Pine(-Ponderosa Pine) Woodland	Open	Small	Clearcut	17	3	14
			Commercial Thinning	22	4	19
			Seed Tree Removal	17	3	14
			Seed Tree Seed Step	7	1	6
			Selection	22	4	19
			Shelterwood Removal	17	3	14
			Shelterwood Seed Step	22	4	19
			Variable Retention	22	4	19
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland	Closed	Large	Clearcut	354	58	297
			Commercial Thinning	161	26	135
			Seed Tree Removal	354	58	297
			Seed Tree Seed Step	325	53	272
			Selection	183	30	153
			Shelterwood Removal	354	58	297
			Shelterwood Seed Step	280	46	234
			Variable Retention	302	49	253
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland	Dense	Large	Clearcut	259	42	216
			Commercial Thinning	93	15	78
			Seed Tree Removal	259	42	216

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
			Seed Tree Seed Step	233	38	195
			Selection	112	18	94
			Shelterwood Removal	259	42	216
			Shelterwood Seed Step	195	32	163
			Variable Retention	214	35	179

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland	Dense	Medium	Clearcut	120	20	101
			Commercial Thinning	130	21	109
			Seed Tree Removal	120	20	101
			Seed Tree Seed Step	101	16	85
			Selection	9	2	8
			Shelterwood Removal	120	20	101
			Shelterwood Seed Step	72	12	60
			Variable Retention	87	14	72

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland	Medium	Large	Clearcut	197	32	165
			Commercial Thinning	60	10	50
			Seed Tree Removal	197	32	165
			Seed Tree Seed Step	176	29	147
			Selection	76	12	64
			Shelterwood Removal	197	32	165
			Shelterwood Seed Step	145	24	121
			Variable Retention	160	26	134

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland	Medium	Medium	Clearcut	72	12	60
			Commercial Thinning	80	13	67
			Seed Tree Removal	72	12	60
			Seed Tree Seed Step	54	9	45
			Selection	80	13	67
			Shelterwood Removal	72	12	60
			Shelterwood Seed Step	27	4	23
			Variable Retention	41	7	34
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland	Medium	Small	Clearcut	48	8	41
			Commercial Thinning	58	9	48
			Seed Tree Removal	48	8	41
			Seed Tree Seed Step	29	5	25
			Selection	58	9	48
			Shelterwood Removal	48	8	41
			Shelterwood Seed Step	1	-	1
			Variable Retention	15	2	13
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland	Open	Medium	Clearcut	24	4	20
			Commercial Thinning	29	5	24
			Seed Tree Removal	24	4	20
			Seed Tree Seed Step	14	2	11

			Selection	29	5	24
			Shelterwood Removal	24	4	20
			Shelterwood Seed Step	29	5	24
			Variable Retention	6	1	5
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Dry-Mesic Mixed Conifer Forest and Woodland	Open	Small	Clearcut	66	11	55
			Commercial Thinning	77	13	64
			Seed Tree Removal	66	11	55
			Seed Tree Seed Step	44	7	37
			Selection	77	13	64
			Shelterwood Removal	66	11	55
			Shelterwood Seed Step	11	2	9
			Variable Retention	28	5	23
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland	Closed	Large	Clearcut	423	69	354
			Commercial Thinning	199	32	167
			Seed Tree Removal	423	69	354
			Seed Tree Seed Step	388	63	325
			Selection	225	37	188
			Shelterwood Removal	423	69	354
			Shelterwood Seed Step	337	55	282
			Variable Retention	362	59	303
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**

Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland	Closed	Medium	Clearcut	156	25	131
			Commercial Thinning	15	2	13
			Seed Tree Removal	156	25	131
			Seed Tree Seed Step	134	22	112
			Selection	31	5	26
			Shelterwood Removal	156	25	131
			Shelterwood Seed Step	102	17	85
			Variable Retention	118	19	99
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland	Dense	Large	Clearcut	272	44	227
			Commercial Thinning	89	14	74
			Seed Tree Removal	272	44	227
			Seed Tree Seed Step	244	40	204
			Selection	110	18	92
			Shelterwood Removal	272	44	227
			Shelterwood Seed Step	201	33	168
			Variable Retention	222	36	186
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland	Dense	Medium	Clearcut	106	17	89
			Commercial Thinning	117	19	98
			Seed Tree Removal	106	17	89
			Seed Tree Seed Step	85	14	71
			Selection	117	19	98

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
			Shelterwood Removal	106	17	89
			Shelterwood Seed Step	54	9	45
			Variable Retention	69	11	58
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland	Dense	Small	Clearcut	118	19	99
			Commercial Thinning	132	21	110
			Seed Tree Removal	118	19	99
			Seed Tree Seed Step	92	15	77
			Selection	132	21	110
			Shelterwood Removal	118	19	99
			Shelterwood Seed Step	52	8	44
			Variable Retention	72	12	60
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland	Medium	Large	Clearcut	199	33	167
			Commercial Thinning	50	8	41
			Seed Tree Removal	199	33	167
			Seed Tree Seed Step	176	29	147
			Selection	67	11	56
			Shelterwood Removal	199	33	167
			Shelterwood Seed Step	142	23	119
			Variable Retention	159	26	133
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**

Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland	Medium	Medium	Clearcut	98	16	82
			Commercial Thinning	107	17	90
			Seed Tree Removal	98	16	82
			Seed Tree Seed Step	79	13	66
			Selection	107	17	90
			Shelterwood Removal	98	16	82
			Shelterwood Seed Step	50	8	42
			Variable Retention	65	11	54
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland	Open	Medium	Clearcut	26	4	21
			Commercial Thinning	32	5	27
			Seed Tree Removal	26	4	21
			Seed Tree Seed Step	13	2	11
			Selection	32	5	27
			Shelterwood Removal	26	4	21
			Shelterwood Seed Step	32	5	27
			Variable Retention	3	1	3
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Lower Montane Black Oak-Conifer Forest and Woodland	Open	Small	Clearcut	27	4	23
			Commercial Thinning	36	6	30
			Seed Tree Removal	27	4	23
			Seed Tree Seed Step	9	1	7
			Selection	36	6	30

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
			Shelterwood Removal	27	4	23
			Shelterwood Seed Step	36	6	30
			Variable Retention	36	6	30
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mesic Mixed Conifer Forest and Woodland	Closed	Large	Clearcut	213	35	179
			Commercial Thinning	34	6	28
			Seed Tree Removal	213	35	179
			Seed Tree Seed Step	186	30	155
			Selection	55	9	46
			Shelterwood Removal	213	35	179
			Shelterwood Seed Step	144	24	121
			Variable Retention	165	27	138
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mesic Mixed Conifer Forest and Woodland	Dense	ExtraLarge	Clearcut	355	58	297
			Commercial Thinning	128	21	107
			Seed Tree Removal	355	58	297
			Seed Tree Seed Step	320	52	268
			Selection	154	25	129
			Shelterwood Removal	355	58	297
			Shelterwood Seed Step	268	44	224
			Variable Retention	294	48	246
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**

Mediterranean California Mesic Mixed Conifer Forest and Woodland	Dense	Large	Clearcut	302	49	253
			Commercial Thinning	149	24	125
			Seed Tree Removal	302	49	253
			Seed Tree Seed Step	279	45	233
			Selection	167	27	140
			Shelterwood Removal	302	49	253
			Shelterwood Seed Step	243	40	204
			Variable Retention	261	43	219

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
Mediterranean California Mesic Mixed Conifer Forest and Woodland	Dense	Medium	Clearcut	93	15	78
			Commercial Thinning	3	-	2
			Seed Tree Removal	93	15	78
			Seed Tree Seed Step	79	13	66
			Selection	13	2	11
			Shelterwood Removal	93	15	78
			Shelterwood Seed Step	58	10	49
			Variable Retention	69	11	58

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
Mediterranean California Mesic Mixed Conifer Forest and Woodland	Medium	ExtraLarge	Clearcut	519	85	434
			Commercial Thinning	396	65	332
			Seed Tree Removal	519	85	434
			Seed Tree Seed Step	500	82	418
			Selection	411	67	344

			Shelterwood Removal	519	85	434
			Shelterwood Seed Step	472	77	395
			Variable Retention	486	79	407
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mesic Mixed Conifer Forest and Woodland	Medium	Large	Clearcut	211	34	176
			Commercial Thinning	76	12	64
			Seed Tree Removal	211	34	176
			Seed Tree Seed Step	190	31	159
			Selection	92	15	77
			Shelterwood Removal	211	34	176
			Shelterwood Seed Step	159	26	133
			Variable Retention	174	28	146
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mesic Mixed Conifer Forest and Woodland	Medium	Medium	Clearcut	81	13	68
			Commercial Thinning	89	14	74
			Seed Tree Removal	81	13	68
			Seed Tree Seed Step	66	11	56
			Selection	89	14	74
			Shelterwood Removal	81	13	68
			Shelterwood Seed Step	44	7	37
			Variable Retention	55	9	46
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**

Mediterranean California Mesic Mixed Conifer Forest and Woodland	Medium	Small	Clearcut	78	13	65
			Commercial Thinning	85	14	71
			Seed Tree Removal	78	13	65
			Seed Tree Seed Step	63	10	53
			Selection	85	14	71
			Shelterwood Removal	78	13	65
			Shelterwood Seed Step	42	7	35
			Variable Retention	52	9	44
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mesic Mixed Conifer Forest and Woodland	Open	Large	Clearcut	69	11	57
			Commercial Thinning	13	2	11
			Seed Tree Removal	69	11	57
			Seed Tree Seed Step	60	10	50
			Selection	20	3	16
			Shelterwood Removal	69	11	57
			Shelterwood Seed Step	47	8	40
			Variable Retention	54	9	45
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mesic Mixed Conifer Forest and Woodland	Open	Medium	Clearcut	25	4	21
			Commercial Thinning	31	5	26
			Seed Tree Removal	25	4	21
			Seed Tree Seed Step	12	2	10
			Selection	31	5	26

			Shelterwood Removal	25	4	21
			Shelterwood Seed Step	31	5	26
			Variable Retention	3	-	2
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mixed Evergreen Forest	Closed	Large	Clearcut	305	50	256
			Commercial Thinning	142	23	119
			Seed Tree Removal	305	50	256
			Seed Tree Seed Step	280	46	234
			Selection	161	26	134
			Shelterwood Removal	305	50	256
			Shelterwood Seed Step	242	40	203
			Variable Retention	261	43	219
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mixed Evergreen Forest	Closed	Medium	Clearcut	184	30	154
			Commercial Thinning	51	8	42
			Seed Tree Removal	184	30	154
			Seed Tree Seed Step	163	27	137
			Selection	66	11	55
			Shelterwood Removal	184	30	154
			Shelterwood Seed Step	133	22	111
			Variable Retention	148	24	124
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
Mediterranean California Mixed Evergreen Forest	Dense	ExtraLarge	Clearcut	651	106	545
			Commercial Thinning	437	71	366
			Seed Tree Removal	651	106	545
			Seed Tree Seed Step	618	101	517
			Selection	462	75	387
			Shelterwood Removal	651	106	545
			Shelterwood Seed Step	569	93	476
			Variable Retention	593	97	496
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mixed Evergreen Forest	Dense	Large	Clearcut	357	58	299
			Commercial Thinning	180	29	151
			Seed Tree Removal	357	58	299
			Seed Tree Seed Step	330	54	276
			Selection	201	33	168
			Shelterwood Removal	357	58	299
			Shelterwood Seed Step	289	47	242
			Variable Retention	310	51	259
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mixed Evergreen Forest	Dense	Medium	Clearcut	149	24	125
			Commercial Thinning	18	3	15
			Seed Tree Removal	149	24	125
			Seed Tree Seed Step	129	21	108
			Selection	33	5	28

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
			Shelterwood Removal	149	24	125
			Shelterwood Seed Step	99	16	83
			Variable Retention	114	19	95
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mixed Evergreen Forest	Medium	Large	Clearcut	128	21	107
			Commercial Thinning	140	23	117
			Seed Tree Removal	128	21	107
			Seed Tree Seed Step	103	17	86
			Selection	140	23	117
			Shelterwood Removal	128	21	107
			Shelterwood Seed Step	66	11	56
			Variable Retention	85	14	71
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mixed Evergreen Forest	Medium	Medium	Clearcut	50	8	42
			Commercial Thinning	58	10	49
			Seed Tree Removal	50	8	42
			Seed Tree Seed Step	33	5	28
			Selection	58	10	49
			Shelterwood Removal	50	8	42
			Shelterwood Seed Step	8	1	6
			Variable Retention	20	3	17
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
Mediterranean California Mixed Evergreen Forest	Medium	Small	Clearcut	34	6	29
			Commercial Thinning	42	7	35
			Seed Tree Removal	34	6	29
			Seed Tree Seed Step	19	3	16
			Selection	42	7	35
			Shelterwood Removal	34	6	29
			Shelterwood Seed Step	42	7	35
			Variable Retention	8	1	7
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Mixed Evergreen Forest	Open	Medium	Clearcut	11	2	10
			Commercial Thinning	17	3	14
			Seed Tree Removal	11	2	10
			Seed Tree Seed Step	-	-	-
			Selection	17	3	14
			Shelterwood Removal	11	2	10
			Shelterwood Seed Step	17	3	14
			Variable Retention	17	3	14
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Red Fir Forest	Dense	Large	Clearcut	379	62	317
			Commercial Thinning	244	40	204
			Seed Tree Removal	379	62	317
			Seed Tree Seed Step	358	58	300
			Selection	259	42	217

			Shelterwood Removal	379	62	317
			Shelterwood Seed Step	327	53	274
			Variable Retention	343	56	287
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Red Fir Forest	Medium	Large	Clearcut	210	34	176
			Commercial Thinning	85	14	71
			Seed Tree Removal	210	34	176
			Seed Tree Seed Step	191	31	160
			Selection	99	16	83
			Shelterwood Removal	210	34	176
			Shelterwood Seed Step	162	26	135
			Variable Retention	176	29	148
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Red Fir Forest	Medium	Medium	Clearcut	86	14	72
			Commercial Thinning	93	15	78
			Seed Tree Removal	86	14	72
			Seed Tree Seed Step	73	12	61
			Selection	7	1	6
			Shelterwood Removal	86	14	72
			Shelterwood Seed Step	52	8	44
			Variable Retention	62	10	52
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**

Mediterranean California Red Fir Forest	Open	Large	Clearcut	118	19	99
			Commercial Thinning	127	21	106
			Seed Tree Removal	118	19	99
			Seed Tree Seed Step	99	16	83
			Selection	12	2	10
			Shelterwood Removal	118	19	99
			Shelterwood Seed Step	72	12	60
			Variable Retention	85	14	72
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Mediterranean California Red Fir Forest	Open	Medium	Clearcut	74	12	62
			Commercial Thinning	81	13	68
			Seed Tree Removal	74	12	62
			Seed Tree Seed Step	61	10	51
			Selection	81	13	68
			Shelterwood Removal	74	12	62
			Shelterwood Seed Step	40	7	34
			Variable Retention	50	8	42
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Northern Rocky Mountain Ponderosa Pine Woodland and Savanna	Medium	Large	Clearcut	89	15	75
			Commercial Thinning	98	16	82
			Seed Tree Removal	89	15	75
			Seed Tree Seed Step	72	12	60
			Selection	98	16	82

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
			Shelterwood Removal	89	15	75
			Shelterwood Seed Step	46	7	38
			Variable Retention	59	10	49
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Northern Rocky Mountain Ponderosa Pine Woodland and Savanna	Medium	Medium	Clearcut	52	8	43
			Commercial Thinning	58	9	48
			Seed Tree Removal	52	8	43
			Seed Tree Seed Step	40	6	33
			Selection	58	9	48
			Shelterwood Removal	52	8	43
			Shelterwood Seed Step	21	3	18
			Variable Retention	30	5	25
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Northern Rocky Mountain Ponderosa Pine Woodland and Savanna	Open	Large	Clearcut	19	3	16
			Commercial Thinning	26	4	22
			Seed Tree Removal	19	3	16
			Seed Tree Seed Step	3	1	3
			Selection	26	4	22
			Shelterwood Removal	19	3	16
			Shelterwood Seed Step	26	4	22
			Variable Retention	26	4	22
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**

Northern Rocky Mountain Ponderosa Pine Woodland and Savanna	Open	Medium	Clearcut	23	4	19
			Commercial Thinning	28	5	24
			Seed Tree Removal	23	4	19
			Seed Tree Seed Step	11	2	9
			Selection	28	5	24
			Shelterwood Removal	23	4	19
			Shelterwood Seed Step	28	5	24
			Variable Retention	2	-	2
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Northern Rocky Mountain Ponderosa Pine Woodland and Savanna	Open	Small	Clearcut	15	2	13
			Commercial Thinning	25	4	21
			Seed Tree Removal	15	2	13
			Seed Tree Seed Step	25	4	21
			Selection	25	4	21
			Shelterwood Removal	15	2	13
			Shelterwood Seed Step	25	4	21
			Variable Retention	25	4	21
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Sierra Nevada Subalpine Lodgepole Pine Forest and Woodland	Medium	Large	Clearcut	202	33	169
			Commercial Thinning	77	13	64
			Seed Tree Removal	202	33	169
			Seed Tree Seed Step	183	30	153
			Selection	91	15	76

Forest Community	Canopy Closure	Height Class	Silviculture Type	Forest Emissions from Harvest (CO2/Acre)	CO2 in Long-Term Wood Products (CO2/Acre)	Net Emissions (CO2/Acre)
			Shelterwood Removal	202	33	169
			Shelterwood Seed Step	154	25	129
			Variable Retention	168	27	141
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Sierra Nevada Subalpine Lodgepole Pine Forest and Woodland	Medium	Medium	Clearcut	158	26	132
			Commercial Thinning	61	10	51
			Seed Tree Removal	158	26	132
			Seed Tree Seed Step	143	23	119
			Selection	72	12	60
			Shelterwood Removal	158	26	132
			Shelterwood Seed Step	120	20	101
			Variable Retention	132	21	110
Forest Community	**Canopy Closure**	**Height Class**	**Silviculture Type**	**Forest Emissions from Harvest (CO2/Acre)**	**CO2 in Long-Term Wood Products (CO2/Acre)**	**Net Emissions (CO2/Acre)**
Sierra Nevada Subalpine Lodgepole Pine Forest and Woodland	Open	Medium	Clearcut	66	11	55
			Commercial Thinning	71	12	60
			Seed Tree Removal	66	11	55
			Seed Tree Seed Step	54	9	45
			Selection	1	-	1
			Shelterwood Removal	66	11	55
			Shelterwood Seed Step	37	6	31
			Variable Retention	46	7	38

8 Statewide Emissions Estimates

The Cal Fire harvest GIS data was used to estimate the number of acres harvested by community and silvicultural method. This was done by overlaying the harvest data on the Landfire data by year (Table 7).

These estimates were then multiplied by the per acre values found in table 6 to produce the following results (Table 8). Spatially explicitly data was only available for private lands; public land harvests were not estimated. However, private lands comprised approximately 90 percent of harvest volumes during this period (FRAP 2010). Harvests associated with timber harvest plans may be implemented over a number of years, however we assumed that harvests occurred in the year of plan approval.

Table 7.Acres by year and silvicultural prescription.

	Silvicultural Prescription							
Year	Clearcut	Commercial Thinning	Seed Tree Removal	Seed Tree Seed Step	Selection	Shelterwood Removal	Shelterwood Seed Step	Variable Retention
2001	34,601	27,687	16,862	2,908	53,033	46,834	134	
2002	39,958	23,606	9,079	1,595	55,560	46,337	125	
2003	38,383	22,325	6,595	2,280	51,367	34,624	96	50
2004	37,270	28,486	8,421	5,647	58,088	42,033	265	448
2005	38,156	30,690	6,413	2,300	64,968	43,275	23	989
2006	36,712	14,930	7,664	1,803	61,888	47,327	59	2,007
2007	31,348	11,508	3,229	922	47,096	18,053	393	1,332
2008	14,554	2,915	1,157	303	15,242	11,375	49	365
Total	**270,983**	**162,148**	**59,422**	**17,759**	**407,241**	**289,858**	**1,144**	**5,192**

The estimates of emissions from this study are intended to be used on a temporary basis for purposes of annual reporting until a revised landscape analysis is conducted. The average annual emissions from this method are approximately three times greater than that estimated in the 2010 FRAP report, which was derived from BOE harvest data. Reasons for this may include the issue of planned versus actual harvest activity. The harvests delineated in timber harvest plans are the maximum allowable and are necessarily implemented at less than that, especially during an economic downturn where some planned harvests may have abandoned. It may be desirable to calibrate these results with reported harvests from the California Board of Equalization by prorating the harvest volumes.

Table 8. Emissions estimates from private lands by year.

Year	Harvest Emission (CO2Mg)	Wood Product Storage (CO2Mg)	Net Emissions (CO2Mg)
2001	18,220,571	2,959,616	15,250,084
2002	19,537,813	3,173,354	16,353,959
2003	19,537,746	3,172,038	16,348,431
2004	23,749,273	3,852,706	19,875,507
2005	23,929,402	3,879,482	20,024,106
2006	22,813,961	3,702,788	19,091,610
2007	16,229,264	2,634,261	13,581,716
2008	6,169,058	1,003,073	5,163,889
Total	**150,187,088**	**24,377,319**	**125,689,302**

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Appendix 4. Carbon time series of wood products from CA forests consumed and discarded instate.

FINAL REPORT

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EXECUTIVE SUMMARY

This report contributes to the project “California Forest and Rangeland Greenhouse Gas Inventory Development”, specifically Task 5 “Develop a time series of California-origin wood products produced and discarded in the state”. The objectives of our analysis included i) a quantification of CA forest harvest volumes, ii) CA wood products consumption from CA-origin wood, and iii) the determination of CA-origin wood carbon (C) in CA landfills and dumps.

Between 1970 and 2010, annual wood harvests in California decreased from 4,566 to around 1,161 million board feet (MMBF). During the same period, wood products consumption rose from 9,652 (1970) to 15,263 (1999) MMBF and declined again to 8,743 MMBF in 2010. Moreover, CA harvests were consistently and considerably below CA consumption for any given year between 1970 and 2010. While CA wood harvests theoretically satisfied over 30% of wood demand in the 1970s, this share steadily declined to below 10% in the 21st century. International export of logs averaged 1.3% over the time period from 1970-2009 and was subtracted from instate CA-origin wood consumption. Interstate log export was not considered due to data uncertainty.

In 2010, around 23 million megagrams (Mg, 10^6 grams or 1 million metric tons) of post 1969 CA-origin wood products were still in use, around 11 million Mg were in landfills and dumps, while around 19 million Mg were emitted to the atmosphere.

Between 2000 and 2009, annual CO_2 emissions from CA-origin wood products in CA landfills and dumps ranged from 665,000 in 2000 to 457,000 Mg CO_2 in 2009 with a consistently decreasing trend (Figure 7). CH4 emissions for the same period ranged between 242,000 to 166,000 Mg CH4 for 2000 and 2009, respectively.

1 INTRODUCTION AND OBJECTIVES

This report contributes to the project "California Forest and Rangeland Greenhouse Gas Inventory Development" (Proposal No. 20113281), Principal Investigator: John Battles. Task 5 of this project "Develop a time series of California-origin wood products produced and discarded in the state" is the focus of this document and specified in the project description as follows:

> *The current ARB GHG inventory for forest, range, and other lands includes releases to the atmosphere from combustion and decay of discarded wood products, including imported wood products. Wood products represent transferred forest carbon from which emissions are delayed until consumption (such as off-site harvest residue combustion for heat and power) or discard (to landfills and composting facilities). The ARB inventory uses landfilled wood products waste characterization data from the Department of Resource Recycling and Recovery (CalRecycle) and a landfill decay model to estimate CO2 and methane generation from the State's landfills; however, the data ARB uses does not categorize wood waste data into California-origin and imported fractions. The model tracks emissions by waste vintage: for any given year, the model calculates emissions from current and prior discards. Historical timber harvest data (used to develop estimates of residues and emissions), methods in Laaksonen-Craig et al. (2003), Smith et al. (2006), Healey et al. (2009) and FRAP (2010) suggest it is possible to develop a time series of the production and discard of California forest-origin wood products. From these, ARB will be able to resolve the California-Origin and imported fractions of wood product decay GHGs emitted from landfills and composting facilities. Since the time period of interest for this scope of work is approximately 2001 through 2010 and wood product decay lifetime in a landfill environment is approximately 30 years, the starting point for developing estimates of California-origin wood product discards is 1970.*

The objectives of our analysis included i) a quantification of CA forest harvest volumes, ii) CA wood products consumption from CA-origin wood, and iii) the determination of CA-origin wood carbon (C) in CA landfills and dumps.

2 METHODS AND DATA

2.1 CA-origin wood products profile

2.1.1 CA forest harvest

We used harvest data from the Board of Equalization (BOE 2012) and the US Forest Service (USFS 2012) to determine total harvest volume in California for the period from 1970 to 2011. For the period from 1970 to 1977, only USFS data was available. For the period from 2001 to 2010, only BOE data was available. For the years covered by both datasets, we averaged harvest data from both datasets.

We used historic conversion rates for board feet (harvested wood) to cubic feet (wood products) provided by Howard et al. 2003. Due to missing data, we used 2002 conversion rates for subsequent years. To convert harvested board feet to carbon equivalents, we employed a factor of 15.11 pounds C per cubic foot provided by Skog and Nicholson (2000) for Pacific Southwest softwood (non-energy wood hardwood production is deminimous in California).

2.1.2 CA wood products consumption

To determine wood products consumption in California, we retrieved US per capita data from Howard (2003) and the US Census Bureau (2012) including all wood product categories such as lumber, plywood and veneer, pulp products and other industrial products. For the years covered by both datasets, we averaged consumption data from both datasets. We sourced historic census data for California from the CA Department of Finance (2012). As the census data is reported in 10 year time steps, we used a linear function to model annual census data.

To determine export of lumber and wood products from California to other US states and abroad, we conducted a literature review.

2.2 C in landfills and dumps

We modeled C disposition patterns in landfills based on Smith et al. (2006; Figure 1) which is identical with the methods applied in the Voluntary Reporting of Greenhouse Gases (1605(b)) Program (DOE 2007). To model C disposition patterns in dumps, which were phased out in 1986, we used methods developed by Skog and Nicholson (2000) who assume that, 65 % of C emitted in first year followed by a linear C emission over 96 years for each new cohort of annual wood waste arriving at a dump (Figure 2).

Based on historical regulatory efforts in the State, we phased out the use of dumps over the ten-year period 1981-1990 (personal communication Klaus Scott at ARB).

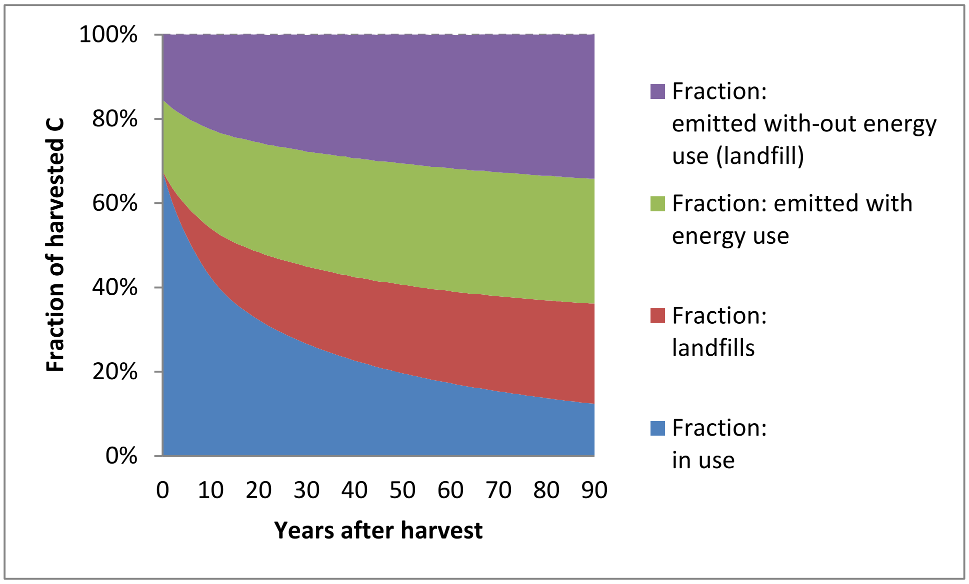

Figure 1. C disposition patterns using landfills (Smith et al. 2006).

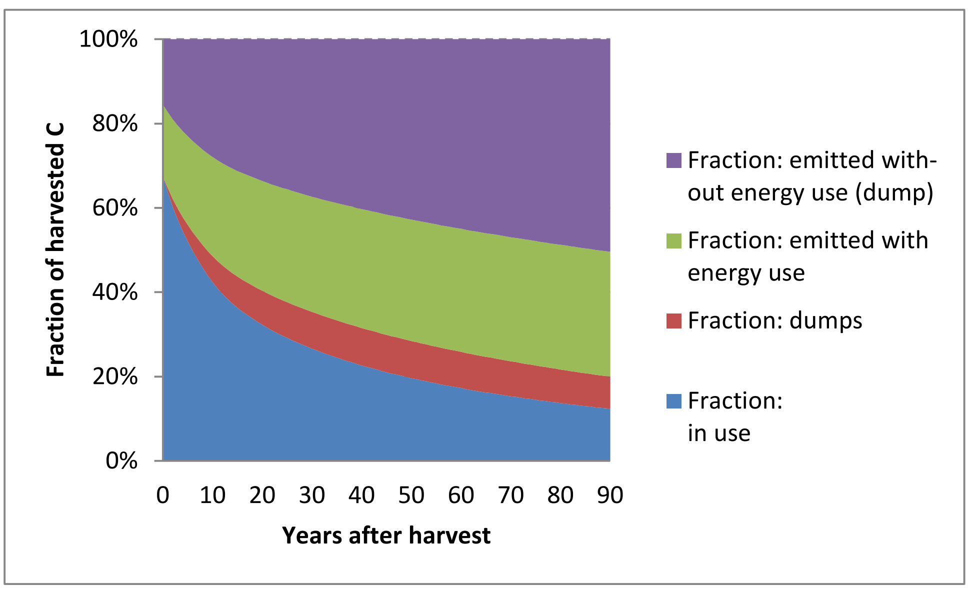

Figure 2. C disposition patterns using dumps (Smith et al. 2006, Skog and Nicholson 2000).

Considerations on wood processing dynamics

While Smith et al. (2006) developed the lookup tables for C fluxes for the characteristic product mix of the second half of the 20th century, a question remained if the point estimates for decay rates as provided by Smith et al. (2006) could be used over a time period of several decades that is characterized by changing conversion efficiencies at the mill as well as changing consumption patterns. For instance, a lower conversion efficiency could be expected in earlier years among mills, while on the demand side a change in consumption patterns could be plausible.

Our results indicate that conversion efficiencies remained fairly constant throughout 1965 to 2002 (Figure 3). While this is less surprising for pulp production, where whole logs are processed and converted to pulp, efficiency gains in sawmill technologies would have suggested otherwise. Between 29 to 38% of total wood products were consumed as pulp (Figure 4) with stable conversion efficiencies throughout the time period examined. Hence, the overall effect of an increase in sawtimber production efficiencies on total wood input would have to be adjusted by the relative share of sawtimber products.

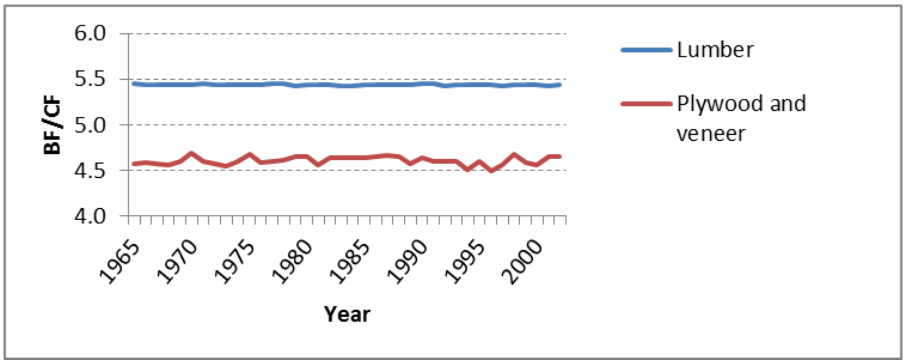

Figure 3. Historic mill conversion efficiencies 1965-2001 (Howard 2003).

Considerations on consumption dynamics

Wood consumption dynamics remained fairly constant throughout the time period observed (Figure 4). Wood product influx to landfill between 1970-2010 can therefore assumed to be fairly stable, resulting – ceteris paribus – in constant decomposition patterns throughout a 100 year period. Moreover, the landfill decomposition data we used in this study (Smith et al. 2006) was based on Skog and Nicholson (2000) who based their estimates on wood consumption percentages by product using historical (1910-1986) and projected fractions (1986-2040).

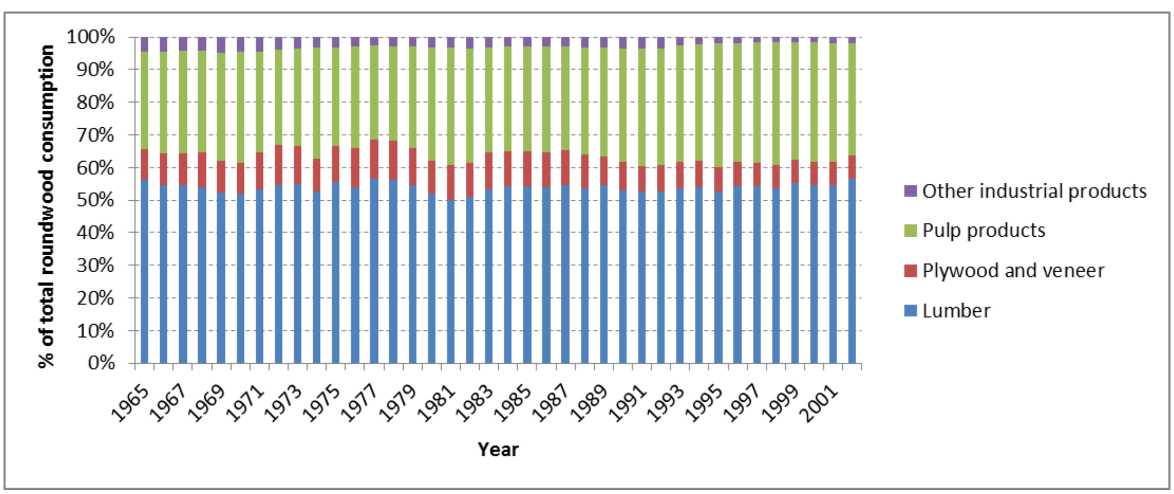

Figure 4. Historic US per capita consumption of wood products 1965-2001 (Howard 2003).

2.3 CO_2 originating from landfills and dumps

To calculate CO_2 emissions, we assumed that half of the C emitted in landfills and dumps would be emitted as CO_2 with the remainder emitted as CH_4 (ARB 2011, p125). In a second step, we compared 2000 to 2009 CO_2 emission estimates with total wood product CO_2 emissions estimated by ARB (ARB 2011).

3 RESULTS AND DISCUSSION

3.1 CA-origin wood products profile

3.1.1 CA forest harvest

Between 1970 and 2010, wood harvests in California decreased from 4,566 to 1,161 MMBF (Figure 5). CA harvest estimates vary by source. For instance, BOE (2012) data was consistently below USFS datasets by an average of 7%. The Western Wood Products Association (FRAP 2010; table 1.2.13) reports numbers ranging 29-38% above BOE datasets. These discrepancies may be explained by different accounting of public and private harvest activities, inclusion of imported logs processed in CA, the application of different conversion rules between board feet and cubic feet, and mill overrun typical for the Scribner board foot scaling rule used in CA.

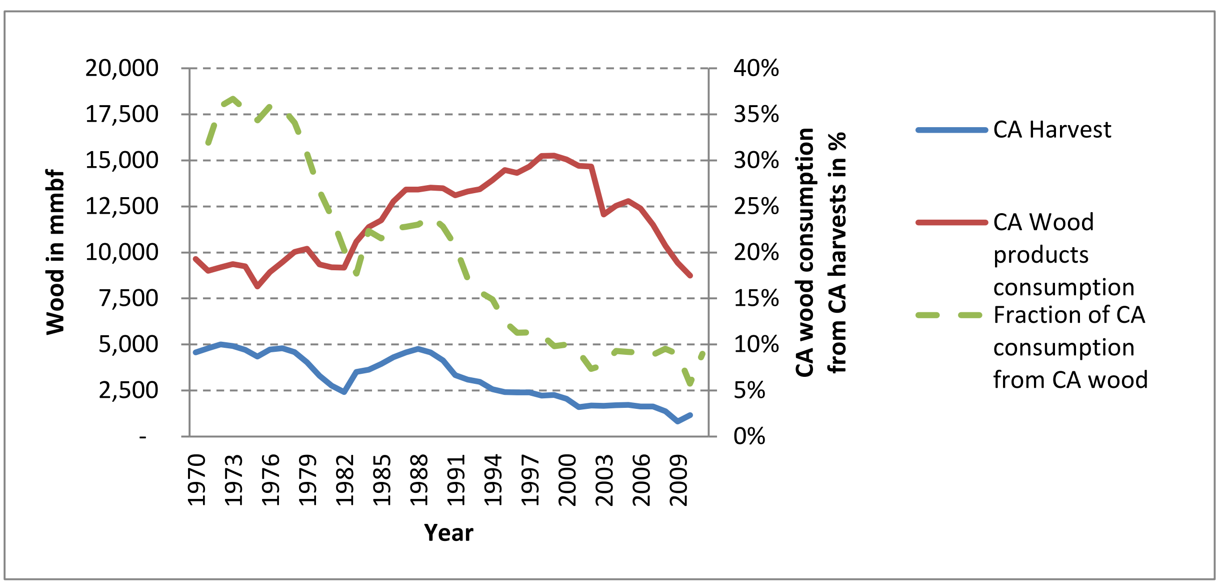

Figure 5. California-origin wood harvest, production and consumption.

Wood sourced from urban and agricultural tree trimmings was not included in the dataset as no reliable data could be found. Wood from these sources is in general of sub-pulpwood quality and does therefore not contribute to the wood products pool with the exception of energy wood which is not relevant to this study.

3.1.2 CA wood products consumption

Consumption

Wood products consumption rose from 9,652 (1970) to 15,263 (1999) MMBF and declined again to 8,743 MMBF in 2010 (Figure 5). To validate these results, we performed a literature review which supported our numbers. For instance, Laaskonen-Craig (2003) assumed 8.5 to 9.9 MMBF lumber consumption in 1999. For the same year, our model combined with wood product consumption data from Howard (2003) suggested a lumber consumption of 8.4 MMBF and a total consumption of 15,263 MMBF. Consumption is cyclical and highly correlated with housing starts and general economic activity.

During this time, CA harvests were consistently and considerably below CA consumption for any given year between 1970 and 2010. While CA wood harvests theoretically satisfied over 30% of wood demand in the 1970s, this share steadily declined to below 10% in the 21st century (Figure 5). This is based on scaled volume for the supply, which historically has a significant overrun as indicated earlier in the comparison to the comparison to the Western Wood Products Association reports.

Export of timber

Between 1970 and 2010, international log exports ranged from 0.2 to 4.2% (2002 and 1970, respectively) and averaged 1.3% over the time period from 1970-2009 where data was available (Morgan et al. 2012 based on data from the Western Wood Products Association). We subtracted this export volume from CA-origin, instate wood products consumption. However, as Morgan et al. (2012) point out, "[WWPA] does not indicate how much, if any, of the wood was actually harvested in California" rather than being logged out of state but shipped from a CA port.

Data on interstate commerce are even more difficult to obtain. Morgan et al. (2012) estimate that in 2006 less than 4% of logs harvested in CA were processed out of state and assume even lower interstate export rates in previous decades: "During 2000 and 2006, less than one-half of harvested timber was processed in its county of harvest, and approximately 82 percent was processed in the resource area of harvest. By comparison, in 1968, 74 percent of the volume harvested and used by California mills was processed in the county where it was harvested, and 92 percent was processed in the resource area of harvest."

3.2 C in landfills

3.2.1 C in landfills and dumps

In 2010, around 23 million Mg (mega grams; equivalent to metric tonnes) of post 1969 CA-origin wood products were still in use, around 11 million Mg were in landfills and dumps, while around 19 million Mg were emitted to the atmosphere (Figure 6). The post 1980 rate increase in C sequestered in dumps and landfills (brown line) can be explained by the longer C residence time in landfills (see Figure 1 and Figure 2) which replace dumps around this time, as well as increasing consumption. According to Smith et al. (2006) the degradable fraction of solid wood has a half-life of 14 years.

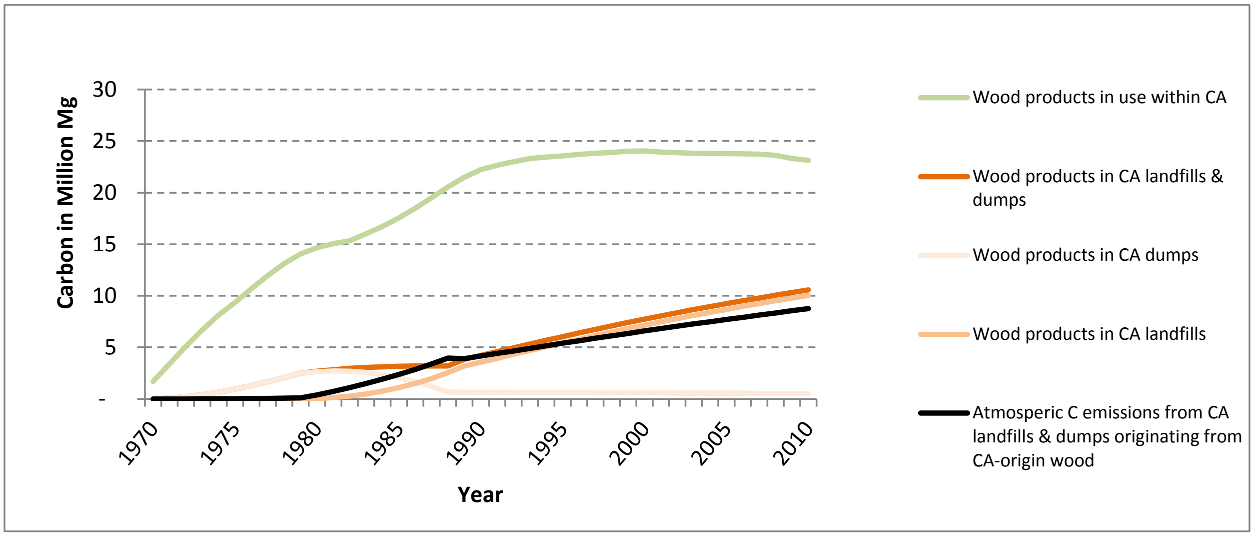

Figure 6. Whereabouts of post-1969 CA-origin wood products.

3.2.2 CO_2 originating from landfills and dumps

Between 2000 and 2009, annual CO2 emissions from CA-origin wood products in CA landfills and dumps ranged from 433,000 in 2000 to 380,000 Mg CO2 in 2009 with a decreasing trend (Figure 7). These CO2 emissions constitute an average of 14% of total wood products emissions from CA landfills and dumps as reported by ARB (2011) for the 2000-2009. CH4 emissions for the same period ranged between 157,000 to 138,000 Mg CH4 for 2000 and 2009, respectively.

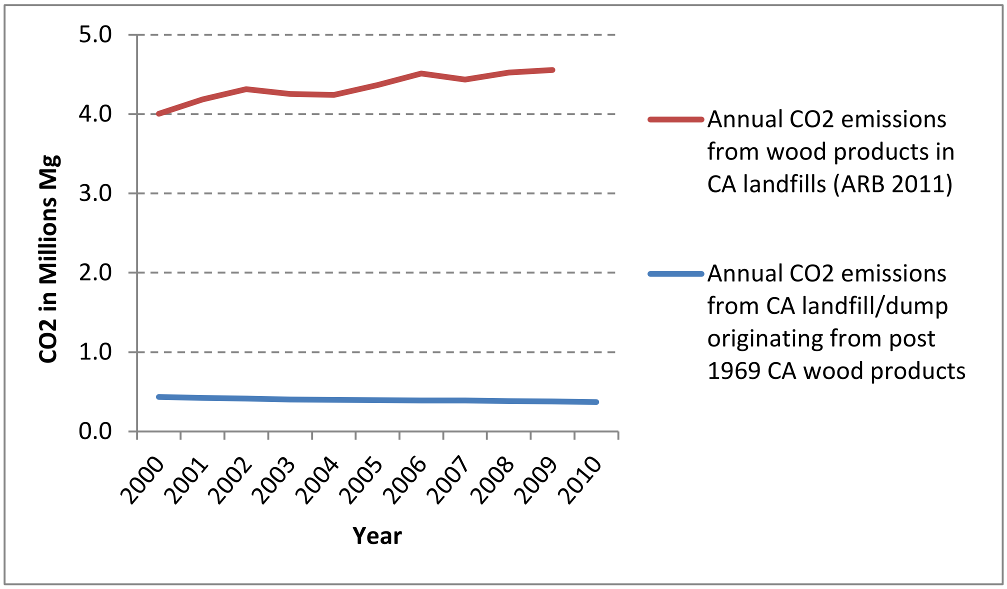

Figure 7. Annual wood-originated CO_2 emissions from California landfills and dumps (non CO_2 emissions excluded).

ACKNOWLEDGEMENTS

We are grateful to Todd A. Morgan, Forest Industry Research Bureau of Business and Economic Research, the University of Montana-Missoula, as well as Xiaoping Zhou and Jean Daniels, Portland Forestry Sciences Lab, USDA Forest Service, for sharing their insights into CA forest product and harvest data.

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