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Aboveground live carbon stock changes of California wildland ecosystems, 2001–2010

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ABSTRACT

The balance between ecosystem emissions of carbon to the atmosphere and removals from the atmosphere indicates whether ecosystems are exacerbating or reducing climate change. Forest ecosystems in the State of California, USA, contain carbon that reaches the highest densities (mass per unit area) in the world, but it has been unresolved whether California ecosystems currently comprise a net sink or source of carbon. The California Global Warming Solutions Act of 2006 established greenhouse gas reduction targets for fossil fuel-burning sectors and ecosystems, underscoring the importance of tracking ecosystem carbon. Here, we conduct statewide spatial inventories of the aboveground live carbon stocks of forests and other terrestrial ecosystems of California, excluding agricultural and urban areas. We analyzed biomass data from field measurements of the Forest Inventory and Analysis program, published biomass information and remote sensing data on non-forest vegetation, and spatial distributions of vegetation types, height, and fractional cover derived by the Landfire program from Landsat remote sensing at 30 m spatial resolution. We conducted Monte Carlo analyses of the uncertainty of carbon stock change estimates from errors in tree biomass estimates, remote sensing, and estimates of the carbon fraction of biomass. The carbon stock in aboveground biomass was 850 ± 230 Tg (mean ± 95% confidence interval) in 2010. We found a net aboveground live carbon stock change of −69 ± 15 Tg from 2001 to 2010, a rate of change of −0.8 ± 0.2% y^{-1}. Due to slow decay of some dead wood, all of the live carbon stock change does not immediately generate emissions. Wildfires on 6% of the state analysis area produced two-thirds of the live carbon stock loss. This suggests that increased tree densities from a century of fire suppression have allowed the accumulation of fuel for carbon losses in recent wildfires. Remote sensing errors in vegetation classification accounted for most of the uncertainty in the carbon stock change estimates. Improvements are also needed to track spatial patterns of growth and dead wood. Our results establish the beginning of a time series for the state greenhouse gas inventory and provide information on the role of forest conservation and management in California in mitigating global climate change.

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1. Introduction

Growing vegetation naturally removes carbon from the atmosphere, reducing the magnitude of climate change. Conversely, deforestation, wildfire, and other agents of tree mortality emit carbon to the atmosphere, exacerbating climate change. Determining the balance between ecosystem carbon emissions to the atmosphere and removals from the atmosphere is essential for tracking the role of ecosystems in climate change (Ciais et al., 2013).

Analyses at coarse spatial resolutions showed net carbon removal by ecosystems globally from 2002 to 2011 (Ciais et al., 2013; Houghton et al., 2012). In contrast, deforestation and forest disturbance have caused net carbon emissions in some parts of the world. In tropical forests, deforestation caused net carbon emissions of 1 Pg y^{-1} from 2000 to 2010 (Baccini et al., 2012). In Canada, wildfire and beetle outbreaks converted forests from a net sink to a source of carbon between 2000 and 2005 (Kurz et al., 2008). In the United States, forests were estimated as a sink from 1990 to 2012 (U.S. Environmental Protection Agency, 2014), but uncertainties in the ecosystem carbon balance remain due to incomplete accounting of non-forest ecosystems (King et al.,

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2012) and the impact of wildfire and other disturbances (Kasischke et al., 2013).

Determining more precisely the carbon balance of California ecosystems is essential for implementing climate change policy because the State of California is one of the few jurisdictions in the world to enact mandatory greenhouse gas emissions reductions. The California Global Warming Solutions Act of 2006 set a goal of reducing state emissions to 1990 levels by 2020. The state set a target for ecosystems (primarily forest ecosystems) of no net loss of carbon by 2020 (ARB, 2008). To accurately measure progress toward this goal, the state has identified minimization of uncertainties in ecosystem carbon estimates as a priority for the state greenhouse gas inventory (ARB, 2014). Spatial data on ecosystem carbon stocks and changes at appropriate spatial and temporal resolutions can also provide natural resource management agencies the data to quantify carbon implications of management activities such as prescribed burning, reforestation, and ecosystem restoration.

Although many studies have examined ecosystem carbon stocks in California, inherent limitations constrain their applicability to the state greenhouse gas inventory. Some consider only forests, excluding the extensive shrublands, grasslands, and other terrestrial ecosystems of the state (Blackard et al., 2008; Cal Fire, 2010; Fried and Zhou, 2008; Kellndorfer et al., 2012; Potter, 2010; Powell et al., 2014; Wilson et al., 2013; Zhang et al., 2014; Zheng et al., 2011). While non-forest ecosystems might contain a relatively small fraction of the total state ecosystem carbon stock, only an analysis that includes all ecosystems can determine this. One study considered forests, shrublands, and grasslands, but covered only part of the state (Brown et al., 2004). Other studies were one-time assessments, precluding calculation of carbon stock change (Blackard et al., 2008; Kellndorfer et al., 2012; Wilson et al., 2013; Zhang et al., 2014). Some rely on process-based models, rather than repeat observations, to estimate trends over time (Brown et al., 2004; Cal Fire, 2010; Potter, 2010; Zhu and Reed, 2012).

Previous efforts do not agree on whether California ecosystems are a net carbon source or sink. Results may differ because of different time periods or different methods. A plot-based analysis of private forests estimated net sequestration from 1984 to 1994, but the authors noted the absence of large fires in the sample area (Fried and Zhou, 2008). Another plot-based sample of forests estimated net sequestration from 1992 to 2001 (Zheng et al., 2011). An analysis of half of the state estimated net sequestration from 1994 to 2000, but most of the sequestration derived from a first approximation of the rate of carbon accumulation in undisturbed forests (Brown et al., 2004). Process-based flux models simulated net sequestration in 2004 (Potter, 2010) and 2005 (Zhu and Reed, 2012) but results were not validated against field data.

In contrast, recent forest carbon estimates at a regional scale have found net emissions from areas that include California. Analyses of inventories of forest biomass, remote sensing of wildfire and vegetation, and aerial surveys of beetle-killed trees across the western U.S. found substantial net carbon emissions from 1984 to 2010 in the California part of the analysis (Hicke et al., 2013). A sample of Landsat remote sensing scenes calibrated against forest inventory plots in California and across the western U.S. found net carbon emissions from western U.S. forests every year from 1986 to 2004 due to timber harvest, wildfire, and trees killed by beetle infestations (Powell et al., 2014).

The high carbon storage potential of ecosystems in California lends importance to determination of their carbon balance. Near Redwood National Park in northern California, coast redwood (*Sequoia sempervirens*) forest reaches an aboveground carbon density of 2900 Mg ha^{-1}, the highest in the world (Busing and Fujimori, 2005). In Sequoia and Kings Canyon National Parks in the Sierra Nevada range of California, giant sequoia (*Sequoiadendron giganteum*) forest reaches carbon densities of up to 2200 Mg ha^{-1} (Blackard et al. 2008).

Our research sought to help address the science, policy, and resource management needs for quantification of California ecosystem carbon through a spatial analysis based on empirical data. Our primary research question: Has the carbon stock of the aboveground biomass of the forests and other terrestrial ecosystems of California, excluding agricultural and urban areas, recently increased or decreased?

2. Methods

2.1. Research approach

We sought to use methods that the California Air Resources Board, the government agency responsible for the state greenhouse gas inventory, could repeat in future years (Battles et al. 2013). Requirements of an operational system include: complete statewide coverage, repeat observations to detect change empirically over time, public availability of data, continuity of data into the future, moderate to fine spatial resolution, moderate to low data processing before analysis, and computational methods feasible for agency personnel.

After evaluating numerous remote sensing options (Battles et al., 2013), we decided that spatial data from the Landfire program (Ryan and Opperman, 2013) most effectively met the criteria. Landfire derives existing vegetation characteristics from Landsat remote sensing data calibrated against field inventories of the Forest Service Forest Inventory and Analysis (FIA) program, the Natural Resources Conservation Service Natural Resource Inventory, the National Park Service fire monitoring program, the U.S. Geological Survey Gap Analysis Program, and other programs. To match international scientific standards, we used methods that comply with the Intergovernmental Panel on Climate Change (IPCC) *National Greenhouse Gas Inventory Guidelines* (IPCC, 2006, 2013).

2.2. Analysis area

To delineate the analysis area, we used Landfire spatial data of vegetation types for 2001 and 2010, the oldest and newest years available at the time of the research. Landfire classifies the existing vegetation type of a pixel through classification tree algorithms that relate field-observed vegetation in a network of field inventory plots to reflectance from seven Landsat spectral bands, topography, and climate variables (Zhu et al. 2006). As vegetation changes, spectral reflectance in the Landsat images also change, leading to reclassification of a pixel. We maintained the Albers Conical Equal Area projection and 30 m spatial resolution of the original data.

For each vegetation type, we determined its IPCC (2006) land category: forest land, wetland, grassland, cropland, settlements, or other land (Table A1). IPCC forest land is land dominated by trees or shrubs, so it includes forests, woodlands, and shrublands. Wetlands are seasonally inundated ecosystems. Grasslands are ecosystems dominated by grasses and forbs. Croplands are lands occupied by annual or perennial agriculture, including orchards. Settlements are land occupied by buildings, paved surfaces, roads, or other urban development. Other land is land not covered by the other categories, including many alpine and desert ecosystem areas.

The forest land, grasslands, wetlands, and other land, excluding cropland and settlements, (hereafter "wildland ecosystems") of the

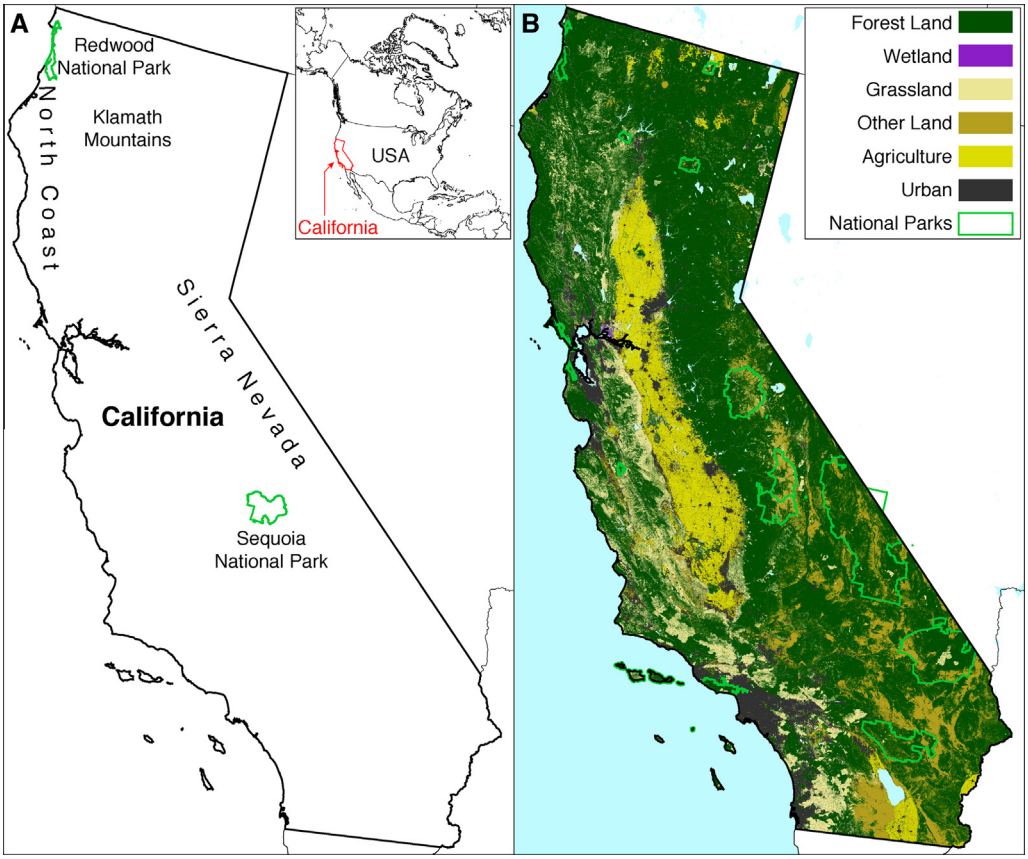

Fig. 1. Analysis area. (a) Location in North America, with map showing places mentioned in the text. (b) Land cover 2010, using Intergovernmental Panel on Climate Change (IPCC, 2006) land categories and vegetation data from Landfire (Ryan and Opperman, 2013).

State of California, USA, constitute the analysis area for this research (Fig. 1). These areas comprise 83% of the 404,500 km^2 land area of the state.

2.3. Biomass densities

We determined the 1083 unique combinations (hereafter "biomass classes") of the three principal Landfire variables – vegetation type, height class, fractional cover class – present in California. The vegetation type of each pixel derives mainly from Landsat remote sensing data (Section 2.2). The Landfire program has defined vegetation types based on the species composition of plant communities that tend to co-occur in environments with similar biophysical characteristics (Ryan and Opperman, 2013). Vegetation falls into increasingly broad hierarchical units of types, subclasses, classes, and orders based on the National Vegetation Classification System (NVCS; Jennings et al., 2009). The NVCS vegetation orders are: tree, shrub, herb, no dominant vegetation, or non-vegetated.

Landfire classifies height and, separately, fractional cover for the dominant herbaceous, shrub, or tree layer of a pixel. Landfire classifies the height and cover of a pixel through regression tree algorithms that relate field-observed height and cover in a network of field inventory plots to reflectance from seven Landsat spectral bands, topography, and climate variables (Zhu et al., 2006). The algorithms estimate height and fractional cover as continuous variables, then group them into classes of ranges of height (herbs 0–0.5 m, 0.5–1.0 m, >1 m; shrubs 0–0.5 m, 0.5–1.0 m, 1.0–3.0 m, >3 m; trees 0–5 m, 5–10 m, 10–25 m, 25–50 m, and >50 m) and cover (0–10%, 10–20%, ...90–100%). As height or cover changes over time, spectral reflectance in the Landsat images also change, leading to reclassification of a pixel.

For each biomass class, we calculated an average aboveground biomass density and standard error (SE), using three separate methods based on NVCS vegetation order (tree, shrub, other). Our analyses focus on the aboveground biomass carbon pool. No independent repeat measurements or remote sensing data of belowground biomass, dead wood, litter, or soil organic carbon are available at the temporal and spatial resolutions of the aboveground biomass data.

For tree-dominated biomass classes, we used plot-level tree biomass estimates from the FIA program, based on FIA field measurements of tree diameter, height, and other variables, from 2001 to 2009 (FIA database version 5.1, November 23, 2011). To maintain consistency with other state government forest carbon estimates, we used tree biomass for the 3623 tree-dominated FIA plots calculated with allometric equations developed for the region (Zhou and Hemstrom, 2009).

In addition, the Forest Service provided us the Landfire vegetation type, height class, and fractional cover class for 2008 (the Landfire data available at the time of the analysis) of each FIA plot in California using the exact geographic coordinates of every plot. This avoided inaccuracies that would result from using the publicly available FIA plot coordinates, which are not the real coordinates of plots since the Forest Service is required by law to maintain the privacy of exact plot locations (McRoberts et al., 2005).

We developed regression equations of aboveground biomass density as a function of Landfire height and fractional cover. We evaluated six models: height or cover only with or without an intercept term and height and cover together with or without an intercept term. The difference between the Akaike's Information Criteria (AIC) value of a given model and the minimum AIC of the six models (an indicator of the best approximating model)

indicated the strength of evidence of each model (Burnham and Anderson, 2002) and favored an equation with height and cover together with an intercept term. The regression equation for the biomass classes based on the 17 major Landfire vegetation types and 5 NVCS subclasses is:

$$\sqrt{B_{\text{vegetation}}} = a + b\ cover + c\ height \tag{1}$$

where $B_{\text{vegetation}}$ is oven-dry plot-level biomass density (Mg ha^{-1}), square-root transformed to correct for positive skew in biomass distribution, a is the intercept, b and c are coefficients, *cover* is the upper limit of the fractional cover class (%), and *height* is the upper limit of the height class (m). We estimated the statistical uncertainty of each biomass density regression equation as a relative error, $E_{\text{regression}}$, equal to the standard deviation (SD) of the regression (Yanai et al., 2010) divided by the mean of plot-level biomass (Table A2). Some Landfire tree-dominated vegetation types are relatively rare and only occur in a few FIA plots. For the five types with less than 30 plots, we derived Eq. (1) by NVCS vegetation subclass.

We used Monte Carlo analysis to quantify the uncertainty of aboveground biomass density estimates from three error sources: (1) variation or error of tree diameter measurement, (2) statistical uncertainty of tree allometric equations, and (3) statistical uncertainty of biomass density regression equations. For the first two sources, we developed an equation of standard error as a function of biomass density, SE_{tree}, from published research that included formal error analysis (Battles et al., 2008; Fahey et al., 2010; Gonzalez et al., 2010; Harmon et al., 2007) (Fig. A1). The tree measurement plots (n = 302) cover the most abundant forest types in California. We used likelihood-based methods (Buckland et al., 1997) to evaluate 11 linear, power, and saturating models and found that the best model was linear (ΔAIC = 11; R^2 = 0.49). For the third source, we used $E_{\text{regression}}$ (Table A2). To estimate the uncertainty from all three sources combined, we calculated 100 realizations of biomass density where each realization included random draws of the distributions of SE_{tree} and $E_{\text{regression}}$. We calculated the standard error of the 100 realizations, $\text{SE}_{\text{biomass}}$, for each tree-dominated biomass class.

For shrubs, we estimated aboveground biomass densities and standard errors from field plot data in the public Landfire reference database and published sources (Table A3). We calculated biomass densities and standard errors of the mean for the 15 most abundant shrub-dominated vegetation types that account for ~90% of total shrub-dominated area. When information was available, we stratified estimates by shrub height class. For the less abundant shrub-dominated vegetation types, we calculated biomass densities and standard errors by NVCS vegetation subclass. For shrub-dominated biomass classes, the standard error estimates only considered plot-level sample variation.

For non-woody vegetation types in California, mainly grassland and arid land ecosystems, no consistent, extensive, biomass inventory data exist that are comparable to the FIA data for trees or the public Landfire reference database for shrubs. Therefore, we calculated aboveground biomass densities and standard errors for non-tree and non-shrub vegetation orders from Moderate Resolution Imaging Spectroradiometer (MODIS) annual net primary productivity (NPP; MOD17A3, Collection 55; Running et al., 2004) for 2000–2010 at 1 km spatial resolution, calibrated by the National Aeronautics and Space Administration to field-measured biomass (Turner et al., 2006) (Fig. A2). After masking pixels obscured by clouds, we calculated, for the 10 non-tree and non-shrub biomass classes, the 2000–2010 mean annual vegetation production (Mg ha^{-1}), the standard error, and the aboveground fraction, using a root:shoot ratio of 4.224 (Mokany et al., 2006). Because most of the standing biomass in these vegetation orders resides in grasses, aboveground NPP provides an approximation of aboveground biomass density (Singh et al., 1975; Sala and Austin, 2000).

2.4. Carbon stocks, changes, and uncertainties

From the original Landfire data, we produced spatial data files of the biomass classes for 2001 and 2010 and calculated land areas. Aboveground live carbon stock ($c_{\text{California}}$, Mg) equals:

$$c^{\text{year}}_{\text{California}} = \sum^{\text{biomass classes}} f_C B_{\text{class}} A^{\text{year}}_{\text{class}} \tag{2}$$

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.

We used Monte Carlo analysis (Gonzalez et al., 2010, 2014) to quantify the uncertainty of carbon stock estimates from three error sources: (1) variation in the carbon fraction of biomass, (2) error in the estimate of biomass by vegetation type, and (3) vegetation type classification error. We calculated 100 realizations of aboveground live carbon stock:

$$\hat{c}^{\text{year}}_{\text{California}} = \sum^{\text{biomass classes}} (f_C + X_{fC}\text{SE}_{fC})(B_{\text{class}} + X_{\text{biomass}}\text{SE}_{\text{biomass}}) \times (A^{\text{year}}_{\text{class}} + X_{\text{area}}\text{SE}_{\text{area}}) \tag{3}$$

where X_{variable} is a random number (different for each variable) from a normal distribution with mean = 0 and SD = 1, and $\text{SE}_{\text{variable}}$ is the standard error of a variable. We estimated SE_{fC} as 5% of the mean (0.0235 g carbon (g biomass)$^{-1}$; McGroddy et al., 2004). $\text{SE}_{\text{biomass}}$ came from the Monte Carlo analyses of aboveground biomass density and NPP analyses described above. SE_{area} is 61% of the mean (Landfire, 2008). The 95% confidence interval (CI) equals:

$$95\%\ \text{CI}_{\text{stock}} = \frac{c^{97.5} - c^{2.5}}{2} \tag{4}$$

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

$$\text{Uncertainty}_{\text{stock}} = \frac{95\%\ \text{CI}_{\text{stock}}}{c^{\text{year}}_{\text{California}}}. \tag{5}$$

We used a stock-change method (IPCC, 2006) to calculate carbon changes. The net live carbon change (Δc_{net}, Mg) for the state equals:

$$\Delta c_{\text{net}} = \sum^{\text{biomass classes}} f_C B_{\text{class}} \left(A^{2010}_{\text{class}} - A^{2001}_{\text{class}}\right). \tag{6}$$

To quantify uncertainty of carbon stock change, the uncertainty guidelines for the IPCC *National Greenhouse Gas Inventory Guidelines* (Frey et al., 2006) have identified two approaches: a simplistic algebraic combination of the uncertainties of two quantities and a Monte Carlo approach that derives the uncertainty from probability density functions of all variables in the stock change equation simultaneously. IPCC recommends the Monte Carlo approach when sufficient data on variable errors and computing processing capabilities are available. Algebraic combination can overstate the uncertainty of carbon change since it gives equal weight to all combinations of errors. In contrast, Monte Carlo analysis uses probability density functions that can give lower weight to less probable error combinations (e.g. all variables showing maximum error at the same time). The supplemental uncertainty guidelines to the IPCC *National Greenhouse Gas Inventory Guidelines* (Pipatti et al., 2013) also identify a major limitation of the algebraic approach to estimating uncertainty of carbon changes: because the denominator of the equation is carbon

change, as carbon change becomes smaller, the denominator approaches zero, producing very high uncertainty values no matter how small the uncertainties of the individual variables may be. Consequently, the algebraic approach gives uncertainty values that do not necessarily reflect the true uncertainty of the carbon change. Therefore, we use the more advanced Monte Carlo approach, as implemented in a previous ecosystem carbon analysis (Gonzalez et al., 2014).

We calculated 100 realizations of the 2001–2010 gross live carbon change:

$$\hat{c}^{2001-2010}_{\text{California}} = \sum^{\text{biomass classes}} (f_C + X_{fC}\text{SE}_{fC})(B_{\text{class}} + X_{\text{biomass}}\text{SE}_{\text{biomass}}) \times \left(\left|A^{2010}_{\text{class}} - A^{2001}_{\text{class}}\right| + X_{\text{area}}\text{SE}_{\text{area}}\right) \quad (7)$$

We then calculated the 95% CI of the gross live carbon change. Uncertainty of live carbon change is the 95% CI of the gross change expressed as a fraction of the gross change:

$$\text{Uncertainty}_{\text{change}} = \frac{95\%\ \text{CI}_{\text{gross change}}}{\sum f_C B_{\text{class}} \left|A^{2010}_{\text{class}} - A^{2001}_{\text{class}}\right|} \quad (8)$$

and the 95% CI of the 2001–2010 net live carbon change of the research area equals:

$$95\%\ \text{CI}_{\text{net change}} = \text{Uncertainty}_{\text{change}} \Delta c_{\text{net}}. \quad (9)$$

Eqs. (7) and (8) use the sum of the absolute values of the changes in land cover area by biomass class to accurately capture the magnitude of change. Because some biomass classes will have a negative change in land area and others will have a positive change as land is converted from one class to another (e.g., as land is converted from shrubland to grassland), the net change could approach zero. The use of absolute values avoids this situation and protects against inaccurately inflating uncertainty in Eq. (8) (Gonzalez et al., 2014).

We analyzed the sensitivity of uncertainty of carbon stock change to the values of the three principal variables by repeating the stock change calculation three times, each time setting the error terms of all but one of the three variables (SE_{fC}, $\text{SE}_{\text{biomass}}$, 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.

To assess the accuracy of our carbon estimates, we validated our results against independent field-and Lidar-derived stocks in coast redwood (Gonzalez et al., 2010) and Sierra Nevada conifer forests (Chen et al., 2012; Gonzalez et al., 2010). We also compared our carbon stock estimates to three other available remote sensing-derived estimates from national analyses (Blackard et al., 2008; Kellndorfer et al., 2012; Wilson et al., 2013). The three national analyses also used some of the same FIA data that we used.

For analyses of carbon stock changes in burned areas, we identified the location of burned areas from 2002 to 2010 wildfire perimeters derived by the Monitoring Trends in Burn Severity program from Landsat remote sensing and field surveys (Eidenshink et al., 2007). For public lands analyses, we used the California Protected Areas Database <http://atlas.ca.gov>. Similar to a previous analysis of carbon in individual U.S. national forests (Heath et al. 2011), we analyzed carbon stocks and changes for the 26 U.S. national parks in California as a case study of ecosystem carbon in protected areas.

3. Results

Average aboveground live carbon density in 2010 for California wildland ecosystems was 26 ± 7 Mg ha^{-1} (mean ± 95% CI). For tree-dominated biomass classes, it was 64 ± 15 Mg ha^{-1}. Average carbon densities for individual biomass classes ranged from 0.08 ± 0.02 Mg ha^{-1} for Sonora-Mojave creosotebush-white bursage desert scrub (height > 3 m, 100% cover) to 600 ± 230 Mg ha^{-1} for California coast redwood forest (height > 50 m, 90–100% cover). The greatest carbon densities occurred in North Coast and Sierra Nevada forests (Fig. 2a).

The net aboveground live carbon stock change in nine years was −69 ± 15 Tg (mean ± 95% CI) (Table 1). Given that the entire range of values was negative, our estimate of a net aboveground live carbon stock decrease was statistically significant (IPCC, 2006, 2013).

Uncertainties of aboveground live carbon for the state analysis area were 26% for the 2001 stock, 27% for the 2010 stock, and 22% for the 2001–2010 stock change (Table 1). Uncertainties were lowest for tree-dominated vegetation.

Aboveground live carbon decreased on 20% of the analysis area and increased on 14% (Fig. 2b). Carbon decreases occurred due to changes in land cover category (Table A4), changes to a lower biomass vegetation type within a land cover category, and reductions in height (14% of the analysis area) and fractional cover (18% of the analysis area). Carbon increases occurred due to changes to higher-biomass land cover categories and vegetation types and vegetation growth as reflected by increases in vegetation height (15% of the analysis area) and fractional cover (13% of the analysis area).

We found that areas burned by wildfires, though a small fraction of state land area and carbon stock, accounted for a disproportionate share of the state carbon stock decrease (Fig. 3). Wildfire and timber harvest areas show clearly in the spatial data on carbon changes (Fig. 4). Most of the carbon stock decrease occurred in the IPCC forest land category, with two-thirds in the NVCS tree vegetation order (Table 1), mainly from wildfires in Klamath Mountains and Sierra Nevada forests (Fig. 2b), and the remaining third from shrub-dominated classes, mainly in extensive wildfires in central and southern California chaparral.

Wildfires and other disturbances converted 9% of the IPCC forest land category to wetlands, grassland, and other non-agricultural and non-urban land (Table A4), generating over half of the state live carbon stock loss. Expansion of agricultural and urban areas claimed ~1% of state wildland area and the associated carbon loss comprised ~3% of the net state carbon loss (Table 1). Net carbon changes within forests that remained forest caused nearly half of state carbon loss (Table 2), with half of the carbon stock loss in burned areas (Table A5).

Carbon stocks decreased on both public and private lands, with carbon stock loss slightly higher on public lands relative to surface area and carbon stock (Fig. 3). Three-quarters of carbon stock loss on public lands came from burned areas while only one-third of carbon stock loss on private lands came from burned areas (Table A5). Within public lands, the 26 U.S. national parks in California conserve 5 ± 2% of the state aboveground carbon stock (Table A6).

Validation of our estimates against independent field- and Lidar-derived stocks quantified in coast redwood and Sierra Nevada mixed conifer forests showed reasonable accuracy, with no statistically significant differences between our results and the independent estimates (Table 3). In addition, comparison of our statewide forest carbon stock estimates with three national remote sensing efforts showed no statistically significant differences with the two most recently published estimates (Table 4). Sensitivity analyses of the major sources of uncertainty showed that vegetation classification error from remote sensing accounted for more of the overall uncertainty than other factors (Table A7).

4. Discussion

Validation of our carbon stock estimates by independent field- and Lidar-derived stocks at three field sites (Table 3) and matching

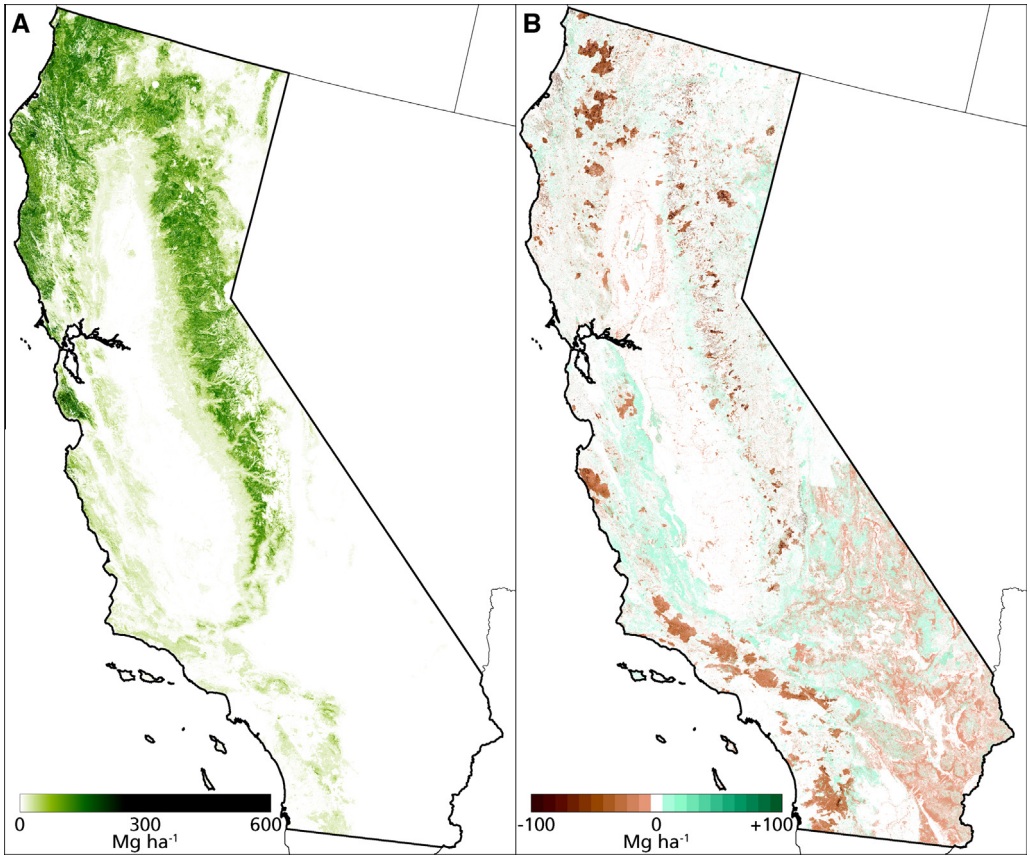

Fig. 2. Carbon in aboveground biomass in forests and other terrestrial ecosystems in California, USA, excluding agricultural and urban areas. (a) Carbon stock 2010. (b) Carbon stock change, 2001–2010.

Table 1
Stocks and changes of carbon in aboveground biomass in forests and other terrestrial ecosystems in California, excluding agricultural and urban areas. Note that 3000 km^2 of forests, wetlands, grasslands, and other land changed to agricultural and urban land.

	2001			2010			2001–2010			
	Carbon Tg	95% CI Tg	Area 10^3 km^2	Carbon Tg	95% CI Tg	Area 10^3 km^2	Carbon Tg	95% CI Tg	Uncertainty %	Area 10^3 km^2
California	920	240	337	850	230	333	−69	15	22	−3
IPCC land categories										
Forest land	915	250	269	840	210	253	−71	19	26	−16
Wetland	<0.5	1	2	<0.5	<0.5	<0.5	<0.5	1	530	−2
Grassland	3	7	27	5	12	41	2	6	280	13
Other land	4	13	59	4	11	59	<0.5	1	240	<0.5
NVCS vegetation orders										
Trees	830	190	125	780	180	122	−48	14	28	−3
Shrubs	89	63	144	66	53	131	−23	14	61	−13
Herbs	3	7	30	5	13	41	2	4	240	11
No dominant life form	<0.5	7	18	1	6	20	<0.5	1	500	2
Non-vegetated	1	7	20	1	8	20	<0.5	<0.5	1300	<0.5

of our forest carbon stock estimates in comparisons with two national remote sensing-derived stocks (Table 4) indicate that our method shows skill in estimating stocks. The Forest Service FIA-based estimate of the 2013 aboveground live carbon stock of California forest land of 950 Tg (http://www.fia.fs.fed.us/Forest%20Carbon/default.asp) is higher than, but within the bounds of our estimate of the 2010 forest land stock of 840 ± 210 Tg.

Although no analysis of uncertainty comparable to ours exists for carbon in California wildland ecosystems, our estimated uncertainties have the same order of magnitude as other published ecosystem carbon analyses. For example, the uncertainty of our 2010 aboveground live carbon stocks was 27%, compared to uncertainties of 6–13% for 2010 aboveground live carbon stocks in tropical forests (Baccini et al., 2012). The uncertainty of our 2001–2010 aboveground live carbon stock change in forest land remaining forest land in California was 35%, compared to a 16% uncertainty for the 2012 aboveground live carbon stock change in forest land remaining forest land in the entire U.S. (U.S. Environmental Protection Agency 2014). All of these uncertainties are based on 95% CI.

The net aboveground live carbon stock decrease that we found for California ecosystems is consistent with a −39 ± 14 Tg carbon stock change in western U.S. forests from 1986 to 2004, documented in an analysis of forest inventory and Landsat remote

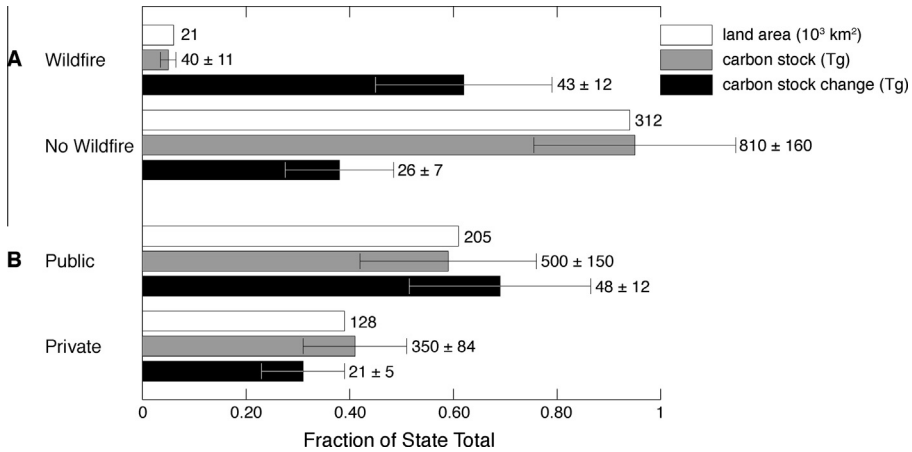

Fig. 3. Comparisons of live carbon stocks and land area (2010) and live carbon stock changes (2001–2010). (a) Wildfire and non-wildfire areas. (b) Public and private lands. Error bars indicate 95% CI from Monte Carlo analysis.

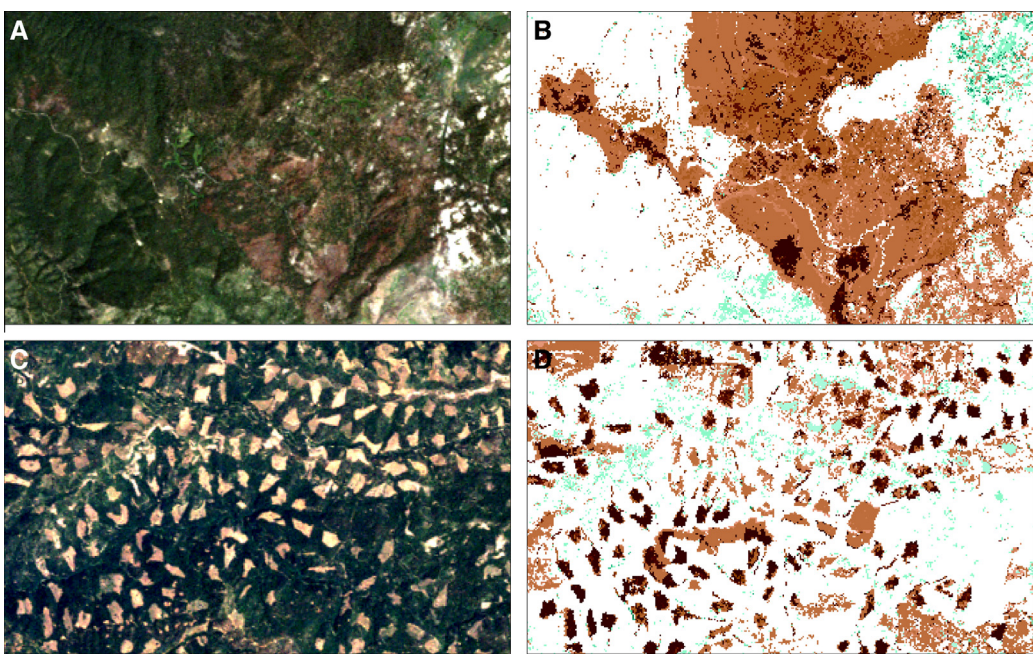

Fig. 4. Aboveground live carbon stock changes through forest disturbance. Area of the Big Meadow fire (August–September, 2009) in Yosemite National Park (image center latitude 37.74, longitude −119.76): (a) Landsat real-color image (August 16, 2010); (b) Carbon stock change, 2001–2010, using the same color scale as Fig. 2b. Area of timber harvest on private land west of Yosemite National Park (image center latitude 38.40, longitude −120.27): (c) Landsat real-color image (July 22, 2009); (d) Carbon stock change, 2001–2010, using the same color scale as Fig. 2b. Each panel is 10.6 km × 6.6 km.

sensing data that explicitly included wildfire (Powell et al., 2014). It is also consistent with a −9% above- and belowground tree carbon stock change in western U.S. forests due to wildfire from 1984 to 2010 and to tree mortality in bark beetle infestations from 1997 to 2010 (Hicke et al., 2013).

The carbon stock decrease that we found runs counter to several previous studies that had estimated carbon sequestration in California wildland ecosystems. Many of the previous efforts that had estimated sequestration only examined forest areas and excluded the shrublands on which extensive fires have burned. Other efforts used process-based flux models rather than empirical repeat measurements or observations to estimate growth. The combination of an underestimation of wildfire and other disturbances and optimistic flux model growth estimates suggests that sequestration was overestimated in many previous estimates.

We recognize, however, several limitations of our methods. Many of these originate in characteristics of the Landfire data. Landfire vegetation classification accuracy is relatively low. In addition, because Landfire height and cover variables are ordinal, not continuous, changes within a single vegetation class takes the form of a step function, limiting detection of changes until the average height or cover of a pixel jumps up or down a class.

The ordinal nature of the Landfire height and cover variables may lead to underestimation by our methods of carbon changes in pixels that experience no change in vegetation type. For fractional cover, Landfire defines ten classes that increase in even steps of 10%. For tree height, the Landfire classes step up more steeply as height increases. If the average height or cover of a pixel changes, but does not cross into the next class, our method records no change (positive or negative) in carbon density. Because growth

Table 2
Stocks and changes of carbon in aboveground biomass in California for major transitions among IPCC land categories and NVCS vegetation orders. Forest–forest = forest land remaining forest land. Forest–natural = net changes between forest land and wetlands, grasslands, and other land. Forest–human = gross changes from forest land to agricultural and urban land. Other natural = wetlands, grasslands, and other land remaining the same. Natural–human = gross changes from wetlands, grasslands, and other land to agricultural and urban land. Tree–tree = tree-dominated remaining tree-dominated. Tree–shrub = net changes between trees and shrubs. Tree–other = net changes between trees and herbs, no dominant, and non-vegetated combined. Shrub–shrub = shrubs remaining shrubs. Shrub–other = net changes between shrubs and herbs, no dominant, and non-vegetated combined. Other–Other = herbs, no dominant, and non-vegetated combined remaining the same. All–human = gross changes to agricultural and urban land.

	2001			2010			2001–2010			
	Carbon Tg	95% CI Tg	Area 10^3 km^2	Carbon Tg	95% CI Tg	Area 10^3 km^2	Carbon Tg	95% CI Tg	Uncertainty %	Area 10^3 km^2
Major transitions among IPCC land categories										
Forest–forest	870	220	246	840	210	246	−29	10	35	0
Forest–natural	42	13	29	4	5	29	−39	11	29	0
Forest–human	2	1	2	0	0	0	−2	1	61	−2
Other natural	4	12	59	4	11	59	<0.5	1	240	0
Natural–human	<0.5	<0.5	2	0	0	0	<0.5	<0.5	190	−2
Major transitions among NVCS vegetation orders										
Tree–tree	790	190	123	770	210	123	−17	5	31	0
Tree–shrub	15	9	7	6	5	7	−9	3	29	0
Tree–other	25	6	6	2	1	6	−23	6	24	0
Shrub–shrub	66	38	116	63	46	116	−3	3	84	0
Shrub–other	17	11	22	2	5	22	−15	10	63	0
Other–other	4	13	59	5	13	59	0.3	0.7	200	0
All–human	2	1	3	0	0	0	−2	1	53	−3

Table 3
Validation of carbon density of aboveground biomass from this research against field- and Lidar-derived results from other research at field sites in California. NR = not reported.

Forest type (site)	Year	Area ha	Carbon density Mg ha^{-1}	95% CI Mg ha^{-1}
Coast redwood (Mailliard State Natural Reserve and Garcia River private forest)		5900		
Gonzalez et al. (2010)	2005		82	1
This research	2001		110	92
Sierra Nevada mixed conifer (North Yuba area of Tahoe National Forest)		5800		
Gonzalez et al. (2010)	2005		140	1
This research	2001		120	68
Sierra Nevada true fir (Sagehen Creek Experimental Forest of Tahoe National Forest)		3500		
Chen et al. (2012)	2005		74	NR
This research	2001		70	30

Table 4
Comparisons of estimates of carbon in aboveground biomass for California forest ecosystems from this research and national remote sensing-based analyses. Areas differ slightly because the comparisons only include areas analyzed by both data sources in each pair and because analyses use data of different spatial resolutions. NR = not reported.

	Years	Spatial resolution m	Area 10^3 km^2	Carbon Tg	95% CI Tg
Blackard et al. (2008)	1990–2003	250	116	970	NR
This research	2001	30	115	730	210
Kellndorfer et al. (2012)	1999–2002	30	119	970	NR
This research	2001	30	119	800	220
Wilson et al. (2013)	2000–2009	250	180	870	NR
This research	2010	30	176	800	190

can occur slowly relative to the nine-year period of our analysis, our methods can underestimate carbon changes due to growth within a cover or height class. Consequently, our stock-change assessment may not completely capture growth as immediately as land cover change.

Recently released data from FIA plots that the Forest Service has resampled over the last decade allow us to approximate our possible underestimate of growth in tree-dominated vegetation. We calculated the plot-level biomass of the 966 plots in California (all tree-dominated) measured in 2001 and 2002 and re-measured 10 years later (FIA database version 6.0, October 2, 2014). Plot-level aboveground biomass increased 6 ± 1% (mean ± SD) over the decade. That first approximation, however, overestimates any growth underestimate of our method because our results already show growth on 14% of state wildland area. Using the first approximation of growth and the worst case of growth underestimation, estimated growth in tree-dominated vegetation types remaining tree-dominated would be ~6 ± 1% of 790 Tg (Table 2) or ~47 ± 8 Tg. If this amount were added to the state carbon balance (−69 ± 15 Tg), California wildland ecosystems would still have experienced a net carbon loss over the decade for all but an implausible extreme case.

Our analysis only examines the aboveground live carbon pool because of the lack of independent repeat field measurements and spatial data of dead wood, other carbon pools, and harvested wood products at the temporal and spatial resolutions of the aboveground biomass data. After a wildfire, much of the carbon will transfer from the aboveground live pool to the dead wood pool. Due to slow decay of some dead wood, all of our estimated aboveground live carbon stock change does not immediately generate emissions. The stock change may indicate committed future emissions that could occur upon complete oxidation of biomass to carbon dioxide (CO_2) or during re-burning of previously burned areas. On the other hand, our estimate of the aboveground live carbon stock change does not include non-CO_2 emissions that occur during a wildfire. These are issues faced by other remote sensing and field inventory-based estimates of aboveground live carbon stock change (e.g. Baccini et al., 2012).

The disproportionate share of the state carbon stock decrease from burned areas demonstrates the importance of wildfire in the carbon balance of California ecosystems. This importance originates in the vast extent of fire-dependent forest and shrub ecosystems across the state and the recent history of fire management. A

century of government policies of complete fire suppression have depressed fire frequencies below natural levels and caused substantial accumulations of biomass and dead matter that can serve as fuel (Marlon et al., 2012). Increased surface and ground fuels have become most pronounced in conifer forests of the western U.S., where small-diameter trees have also increased considerably (Stephens et al., 2007; Marlon et al., 2012). These increases have contributed to the recent occurrence of uncharacteristically large and severe wildfires (Stephens et al., 2014). Our finding of a carbon stock decrease occurring largely in areas burned by wildfire suggests that increased tree densities from a century of fire suppression have allowed the accumulation of fuel for carbon losses in recent wildfires.

A short-term emissions increase may be difficult to avoid because natural resource management agencies that are working to restore ecologically appropriate fire regimes use prescribed burning and managed wildland fire (intentionally allowing lightning-ignited fires to burn in targeted areas) – practices that emit carbon in the short term. Moreover, if the world does not reduce greenhouse gas emissions from cars, power plants, and other fossil fuel-burning human activities, projections indicate that climate change may increase wildfire frequencies by one-third to three-fourths across much of California (Westerling et al., 2011). These findings support a management strategy of reducing fuel loads to minimize the future potential of catastrophic fires under climate change. Although prescribed burning, managed wildland fire, and mechanical fuel reduction treatments across public and private lands may release greenhouse gases in the short term, these practices can augment carbon storage in the long term by shifting growing space from many small trees to fewer large, old trees and also enhance resilience to stress and disturbance (Hurteau and Brooks, 2011; Collins et al., 2014; Hurteau et al., 2014) and potential increases in wildfire frequency due to climate change (Moritz et al., 2012).

The spatial data on carbon stocks that we have produced can provide information to assess the ecosystem service of carbon storage for mitigating climate change. As an example, our results show that the U.S. national parks in California store 42 ± 15 Gg of carbon in aboveground biomass (Table A6). A direct measure of the ecosystem service that these protected areas provide is the equivalent number of people whose annual greenhouse emissions this storage represents. Based on total U.S. greenhouse gas emissions (U.S. Environmental Protection Agency, 2014) and U.S. population (U.S. Bureau of the Census, 2013), average carbon emissions per capita in 2013 in the U.S. were 5.6 ± 0.3 Mg person^{-1} year^{-1}. Therefore, the U.S. national parks in California store an amount of carbon equivalent to the annual emissions of 7.4 ± 2.6 million people in the U.S.

Our finding of a net carbon stock decrease runs opposite to the goal that the state programmed in its initial scoping plan for emissions reductions (ARB, 2008). The state initially estimated net sequestration of carbon in aboveground and belowground biomass in state ecosystems and set a minimum goal of no net emissions by 2020. Our results show that aboveground live carbon losses from ecosystems are as much as 5–7% of state carbon emissions from all sectors. This reversal suggests a new emissions reduction challenge. A suite of forest management strategies, including conservation of high-biomass forests, fire management adapted to future climate change, and reforestation of areas cut for timber, may be necessary for meeting goals for 2020 and beyond.

Our results provide spatial estimates of aboveground live carbon stock changes and uncertainties for the wildland ecosystems of California, furnishing data for the state scoping plan for emissions reductions (ARB, 2014). Because the Landfire program has begun to produce vegetation data every two years, our analysis establishes the beginning of a time series to track aboveground live carbon in wildland ecosystems. Our research points to three main areas for improving future greenhouse gas inventories. First, increased remote sensing accuracy of vegetation type identification would reduce the uncertainty of carbon estimates. Landfire plans to address this need through improved ground-truthing of vegetation types for the 2014 data layer. Second, a more finely resolved way to account for forest growth is needed. If the Landfire program released its height and cover estimates in their original forms as continuous variables, it would be possible to track growth more closely. In the absence of those continuous variables, the subset of FIA plots that are re-measured provide empirical data to design and test potential techniques. Third, empirical spatial estimates of dead wood and other carbon pools over time would allow for a more comprehensive carbon inventory.

Our results provide spatial data for natural resource management agencies to evaluate carbon consequences of fire management and restoration activities and to assess the ecosystem service of carbon storage. In contrast to the net removal of carbon from the atmosphere by ecosystems at a global scale, the results for California illustrate how carbon stock losses from wildfires can potentially exceed carbon sequestration at a local scale.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foreco.2015.03.040.

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