California Vegetation Carbon Changes and Uncertainties 2001-2008

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Abstract

The State of California conducts an annual inventory of greenhouse gas emissions and removals to track its progress in reducing the anthropogenic emissions that cause climate change. To provide robust estimates of carbon stocks and changes in forests, grasslands, wetlands, and other natural land areas, we analyzed Forest Inventory and Analysis program data, land cover derived from Landsat remote sensing for the Landfire program, and net primary productivity derived from Moderate Resolution Imaging Spectroradiometer (MODIS) remote sensing. The analysis excluded agricultural and urban land. We quantified uncertainties of carbon estimates through Monte Carlo analyses of statistical variation in biomass allometric equations and inventory sampling, variation in the carbon fraction of biomass, and land cover classification error. Carbon in aboveground biomass (mean ± 95% confidence interval [CI]) decreased from 920 ± 240 million Mg (1 Mg = 1 ton) in 2001 to 900 ± 260 million Mg in 2008. The 2001-2008 change in aboveground live carbon was -21 ± 5 million Mg. Because the entire range of values of 2001-2008 net carbon change was negative (-26 to -16 million Mg), the net emissions were significant. Most of the emissions occurred in shrub ecosystems, 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 emissions in other ecosystems. The 26 U.S. national parks in California conserve 5% of the aboveground live carbon in the state. While public lands cover 60% of the area of natural lands, they accounted for only half of the carbon emissions. So, private lands generated a disproportionate share of carbon emissions. Validation of our aboveground live carbon stock estimates against field-derived stocks at sites in coast redwood forest and Sierra Nevada mixed conifer forest showed accuracy of our results. Comparison of our statewide estimates against three other remote sensing-derived efforts showed agreement with the two most recent estimates. 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.

Introduction

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

Vegetation naturally removes greenhouse gases from the atmosphere, reducing the magnitude of climate change. Global 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).

In response to climate change, the State of California in 2006 enacted the Global Warming Solutions Act (Assembly Bill 32). The Act sets greenhouse gas emissions reduction targets and requires a periodic inventory of greenhouse gas emissions to and removals from the atmosphere. The California Air Resources Board (ARB) has produced one greenhouse gas inventory of forests and agriculture (CEC 2004).

California hosts forests with some of the highest carbon densities (carbon mass per unit area) in the world (Aalde et al. 2006) and the U.S. National Park Service (NPS) manages many of these high-carbon forests. Coast redwood (*Sequoia sempervirens*) has attained carbon densities of up to 2900 Mg ha^{-1} just south of Redwood National Park in Humboldt Redwoods State Park (Busing and Fujimori 2005). Giant sequoia (*Sequoiadendron giganteum*) has attained carbon densities of up to 2200 Mg ha^{-1} in Sequoia and Kings Canyon National Parks (Blackard et al. 2008).

California ARB and NPS managers of high-carbon forest ecosystems both require scientifically robust estimates of vegetation carbon changes and uncertainties over time. Ideally, these estimates should conform to the international standard methods that the IPCC has developed for greenhouse gas inventories (IPCC 2006, 2013b) and which countries use for consistent reporting under the U.N. Framework Convention on Climate Change. We have sought to address these needs through two research objectives: (1) To quantify stocks, changes, and uncertainties of carbon for all land in the State of California, except for agricultural and urban areas, from 2001 to 2008 and (2) To assess the relative contributions of different factors to overall uncertainties of estimates of carbon change.

Methods

General Approach

The California greenhouse gas inventory consists of annual estimates of emissions to and removals from the atmosphere for the entire state, produced by the staff of California ARB. In addition, national park and other field managers need spatial data to apply carbon analysis results to natural resource management. These needs established the operational requirements for our data sources and methods, including:

- 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
- Low data processing before analysis.

Published vegetation carbon research commonly calculates carbon stocks as the product of surface areas of land cover types, classified by satellite remote sensing, and the carbon densities, derived from field measurements of trees and allometric equations, summed over all land cover types (e.g. 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, generally five to twenty classes (e.g. Bartholomé and Belward 2005, Loveland et al. 2000), can limit the possible carbon density of each pixel to a few discrete values.

In contrast, other methods use Light Detection and Ranging (Lidar) or high-resolution satellites such as QuickBird, Ikonos, or WorldView to sense physical dimensions of trees to which aboveground biomass directly correlates (e.g. Gonzalez et al. 2010, Saatchi et al. 2011). 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.

Potential errors and variation of remote sensing data, allometric biomass equations, and other key components of forest carbon estimation render necessary a careful quantification of uncertainty. This provides the data to ascertain if estimated net changes in greenhouse gas emissions and removals over time are statistically significant. In addition, quantification of the contribution of individual variables to uncertainty can point to how strengthening specific links in the chain of methods could reduce overall uncertainty. To quantify uncertainty, the Intergovernmental Panel on Climate Change (IPCC 2006) recommends Monte Carlo analysis, yet only a few forest carbon research efforts have applied this approach (e.g. Gonzalez et al. 2010, Monni et al. 2007). Monte Carlo analysis is a method to quantify the cumulative errors from forest inventory, biomass regression equations, carbon fraction of biomass, and remote sensing accuracy into one measure (95% CI), as previously demonstrated for high biomass forests in California (Gonzalez et al. 2010).

Our analysis proceeded through three parts: (1) Remote sensing of vegetation, (2) calculation of biomass densities, and (3) calculation of carbon stocks, stock changes, and uncertainties. Within each part, we assessed different data sources and methods for the requirements of an operational greenhouse gas inventory system. The area of analysis is the entire area of the State of California, except for agricultural and urban land.

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.

We assessed 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) 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 vegetation types (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 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 downloading and testing different sets of land cover and vegetation level remote sensing, the advantages of Landfire data became clear. USGS has completely processed and calibrated the data against field measurements, posted the data publicly, and provided three different years with continuing plans for future releases. Moreover, the Landfire variables are developed together, providing an internally consistent treatment of both land cover and vegetation level. While biomass densities can be derived for Landfire forest types from U.S. Department of Agriculture Forest Service forest inventory data (see next subsection), Landfire grassland and other vegetation types do not have an analogous consistent set of field data. Therefore, we decided to use NASA MODIS NPP to calculate biomass densities for non-forest vegetation types.

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 examined each Landfire vegetation type and recorded the IPCC (2006) land category to which it belonged: forest land, wetland, grassland, other land (natural ecosystems), cropland, and settlements. In parallel, the Landfire program assigned each vegetation type to a National Vegetation Classification System (NVCS, Jennings et al. 2009) suborder: tree, shrub, herb, no dominant vegetation, and non-vegetated.

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>.

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. From the existing mask of the analysis area, we masked out MODIS pixels with cloud cover in any individual year.

Calculation of Biomass Densities

John Battles analyzed U.S. Department of Agriculture Forest Service Forest Inventory and Analysis (FIA) data to derive aboveground biomass per unit area (biomass density) of as many combinations of Landfire vegetation type, height class, and cover class as had statistically valid sample sizes. (A separate report provides details of those analyses). Since 2000, Federal legislation has prohibited the Forest Service from publicly releasing exact coordinates of FIA plots due to privacy concerns. To ensure the accuracy of our biomass densities, we collaborated with the Forest Service, who provided us the Landfire vegetation type, height class, and cover class of each plot in California using the exact geographic coordinates. They did not release coordinates to us, only the Landfire values for the exact plot locations. John Battles also calculated statistical variation and errors from biomass allometric equations and inventory sampling. For shrub vegetation types not covered by FIA, John Battles compiled published estimates of aboveground biomass. For other biomass pools, he used published root-to-shoot ratios (Mokany et al. 2006) to calculate belowground biomass and modeled estimates for deadwood and litter. (Again, John Battles provides details of those analyses in a separate report.) These analyses produced two biomass densities for each biomass class: aboveground live and total.

For wetlands, grasslands, and other natural land classes, 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 grasses in these land classes, mean annual aboveground vegetation production is approximately equal to aboveground standing biomass.

Calculation of Carbon Stocks, Stock Changes, and Uncertainties

We compiled biomass densities and standard errors for forest, shrub, wetland, grassland, and other natural land classes into a single table. Each combination of the three Landfire variables (vegetation type, height class, cover class) with a unique biomass density constituted a biomass class. A number of Landfire vegetation types, height classes, and cover classes did not end up in one of the biomass classes. We combined those vegetation types, height classes, and cover classes into types and classes that were part of the biomass classes.

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:

$$c_{\text{California}}^{\text{year}} = \sum^{\text{biomass classes}} f_{\text{C}} B_{\text{class}} A_{\text{class}}^{\text{year}} \quad \text{(Equation 1)}$$

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. 1. 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:

$$c_{\text{California}}^{\text{year}} = \sum^{\text{biomass classes}} \left(f_{\text{C}} + X_{f\text{C}} \text{SE}_{f\text{C}}\right)\left(B_{\text{class}} + X_{\text{biomass}} \text{SE}_{\text{biomass}}\right)\left(A_{\text{class}}^{\text{year}} + X_{\text{area}} \text{SE}_{\text{area}}\right) \quad \text{(Equation 2)}$$

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 of John Battles. 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:

$$95\% \text{ CI}_{\text{stock}} = \frac{c^{97.5} - c^{2.5}}{2} \quad \text{(Equation 3)}$$

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:

$$\text{Uncertainty}_{\text{stock}} = \frac{95\% \text{ CI}}{c_{\text{California}}} \quad \text{(Equation 4)}$$

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

$$\Delta c_{\text{net}} = \sum^{\text{biomass classes}} f_{\text{C}} B_{\text{class}} (A_{\text{class}}^{2008} - A_{\text{class}}^{2001}) \qquad \text{(Equation 5)}$$

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

$$c_{\text{California}}^{\text{2001-2008}} = \sum^{\text{biomass classes}} \left(f_{\text{C}} + X_{f\text{C}} \text{SE}_{f\text{C}}\right)\left(B_{\text{class}} + X_{\text{biomass}} \text{SE}_{\text{biomass}}\right)\left(\left|A_{\text{class}}^{2008} - A_{\text{class}}^{2001}\right| + X_{\text{area}} \text{SE}_{\text{area}}\right) \qquad \text{(Eq. 6)}$$

Equation 4 gives the 95% CI of the gross carbon change. Uncertainty of carbon change equals:

$$\text{Uncertainty}_{\text{change}} = \frac{95\%\ \text{CI}_{\text{gross change}}}{\sum^{\text{biomass classes}} B_{\text{class}} \left|A_{\text{class}}^{2008} - A_{\text{class}}^{2001}\right|} \qquad \text{(Equation 7)}$$

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

$$95\%\ \text{CI}_{\text{net change}} = \text{Uncertainty}_{\text{change}} \Delta c_{\text{California}}^{2001-2008} \qquad \text{(Equation 8)}$$

We also used equations 1-8 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 field-derived stocks in coast redwood at Mailliard Redwoods State Natural Reserve and the private Garcia River forest in Mendocino County and Sierra Nevada mixed conifer forest in the North Yuba area of Tahoe National forest (Gonzalez et al. 2010).

We also compared our statewide aboveground live carbon estimates against three other remote sensing-derived estimates (Blackard et al. 2008, Kellndorfer et al. 2012, Wilson et al. 2013). This was note validation because these other estimates were not from field measurements.

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 [$\text{SE}_{f\text{C}}$], 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.

Results

The analysis area covers 337 300 km^2, 83% of the 404 500 km^2 land area of the state (Figure 1). We combined Landfire vegetation types, height classes, and cover classes into approximately half the original number (Table 1) and defined 1083 biomass classes. NPP (mean ± standard deviation [SD]) for 2000-2010 was 5 ± 0.5 Mg ha^{-1} y^{-1} (Figure 2). The change in NPP (mean ± SD) between 2001 (average of 2000-2003) and 2008 (average of 2007-2010) was -1% ± 10% (Figure 3).

The average aboveground live carbon density of the state is 27 ± 8 Mg ha^{-1} (Table 2). Aboveground live carbon (Figures 3 and 4) decreased ~2% and total carbon decreased ~4% from 2001 to 2008 (Figure 5), with uncertainties of 19-29% for stocks and 21-25% for changes (Table 3). Most of the emissions occurred in the forest IPCC land category, with a slight increase in the grassland category (Tables 4 and 5). Forests that remained forest during the period accumulated carbon slightly (Table 6). Within forests, most of the emissions occurred in the NVCS shrub vegetation order (Tables 7 and 8). 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).

Validation of our aboveground live carbon estimates showed that the 95% CI range of our estimates encompassed field-derived stocks in Mailliard Redwoods State Natural Reserve, Garcia River forest in Mendocino County, and the North Yuba area of Tahoe National forest (Table 12). Comparisons of our estimates with other remote sensing-derived estimates showed that the 95% CI range of our estimates encompassed the two most recently published estimates (Kellndorfer et al. 2012, Wilson et al. 2013), but was lower than the oldest estimate (Blackard et al. 2008) (Table 13).

Sensitivity analyses showed that overall uncertainty decreased the least when all errors except Landfire land classification error from remote sensing were set to zero and when setting Landfire land classification error from remote sensing to zero (Table 14).

Discussion

Because the entire range of values of 2001-2008 net carbon change was negative (-26 to -16 million Mg), the net emissions were significant. While the 95% CIs of the carbon stock estimates for individual years show some overlap, the proper measure for evaluating the significance of carbon change is the directly-calculated 95% CI of the 2001-2008 net carbon change.

Carbon decreases from wildfires were visible in the spatial analyses of MODIS NPP (Figure 3) and Landfire (Figure 6) data. Close-up views of the Landfire results showed fire scars and timber harvesting areas (Figure 7). Most of the estimated emissions occurred in shrub ecosystems, 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 emissions in other ecosystems.

The 95% CI of aboveground live carbon showed similar spatial patterns (Figures 8 and 9) as the carbon densities (Figures 4 and 5), with values highest in the forests of the coastal ranges, the Klamath Mountains, and the Sierra Nevada.

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 emissions.

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.

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Table 1. Vegetation classes.

	Vegetation Type	Height Class	Cover Class
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. Aboveground carbon densities (Mg ha^{-1})

	mean	95% CI
California	27	8
Redwood National Park	160	78
IPCC land categories		
forests	35	8
wetland	1	4
grassland	1	2
other land	0.3	3
NVCS vegetation orders		
tree	67	18
shrub	5	3
herb	1	3
no dominant	0.2	4
non-vegetated	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. Carbon stock changes and uncertainties across the State of California, 2001-2008, by IPCC land category.

	Aboveground live			**Total**			**Sample**	
	Mean (10^6 Mg)	95% CI (10^6 Mg)	Change (%)	Mean (10^6 Mg)	95% CI (10^6 Mg)	Change (%)	(classes)	(10^6 pixels)
Forests remaining forest	+21	6	+2	+29	7	+1	806	47
Forests and other natural lands (net change)	-23	11	-83	-76	29	-77	653	5
Forests and human lands (gross change)	-17	4	NA	-49	12	NA	664	5
Other natural lands (net change)	-0.02	0.04	~0	-0.08	0.06	~0	20	3
Other natural lands and human lands (gross change)	-0.2	0.4	NA	-1	0.8	NA	13	2
California natural ecosystems (net change)	-21	5	-2	-100	26	-4	800	74

Table 7. 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 8. 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 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.

	2001	2001	2008	2008	2008	2008	2001-2008	2001-2008	2001-2008
	Stock	95% CI	Stock	95% CI	Area	Carbon Density	Change	95% CI	Area
National Park	(10^6 Mg)	(10^6 Mg)	(10^6 Mg)	(10^6 Mg)	(km^2)	(Mg ha^{-1})	(10^6 Mg)	(10^6 Mg)	(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 field-derived estimates.

	Area (ha)	Carbon density (Mg ha^{-1})	95% CI (Mg ha^{-1})
North Yuba	5800		
Gonzalez et al. (2010)		140	1
This research		120	70
Garcia-Mailliard	5900		
Gonzalez et al. (2010)		82	1
This research		120	80

Table 13. Comparison of aboveground live tree carbon estimates for the State of California with other spatial estimates.

	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 Monte Carlo sensitivity of 2001-2008 change in aboveground live carbon to variable error. All results expressed as a fraction (%) of the mean.

situation	SE fC	SE biomass	SE Landfire	uncertainty 2001-2008
best estimate	5	1-120 (trees, shrubs); 86-770 (other)	61	21
carbon fraction error only	5	0	0	9
biomass error only	0	1-120 (trees, shrubs); 86-770 (other)	0	11
Landfire error only	0	0	61	15
no carbon fraction error	0	1-120 (trees, shrubs); 86-770 (other)	61	18
no biomass error	5	0	61	17
no Landfire error	5	1-120 (trees, shrubs); 86-770 (other)	0	16

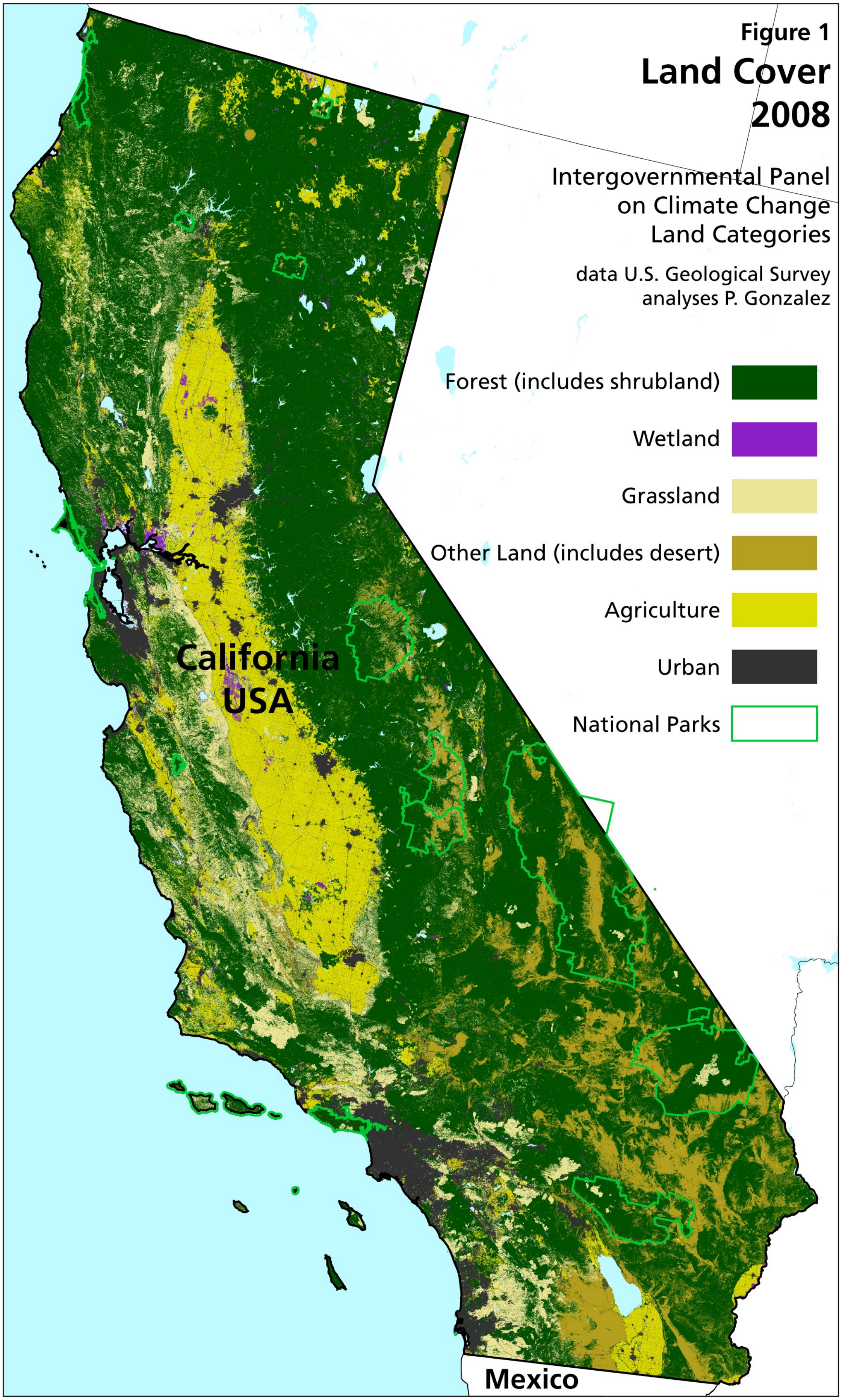
Figure 1
Land Cover
2008
Intergovernmental Panel
on Climate Change
Land Categories
data U.S. Geological Survey
analyses P. Gonzalez
Forest (includes shrubland)
Wetland
Grassland
Other Land (includes desert)
Agriculture
Urban
National Parks
California
USA
Mexico

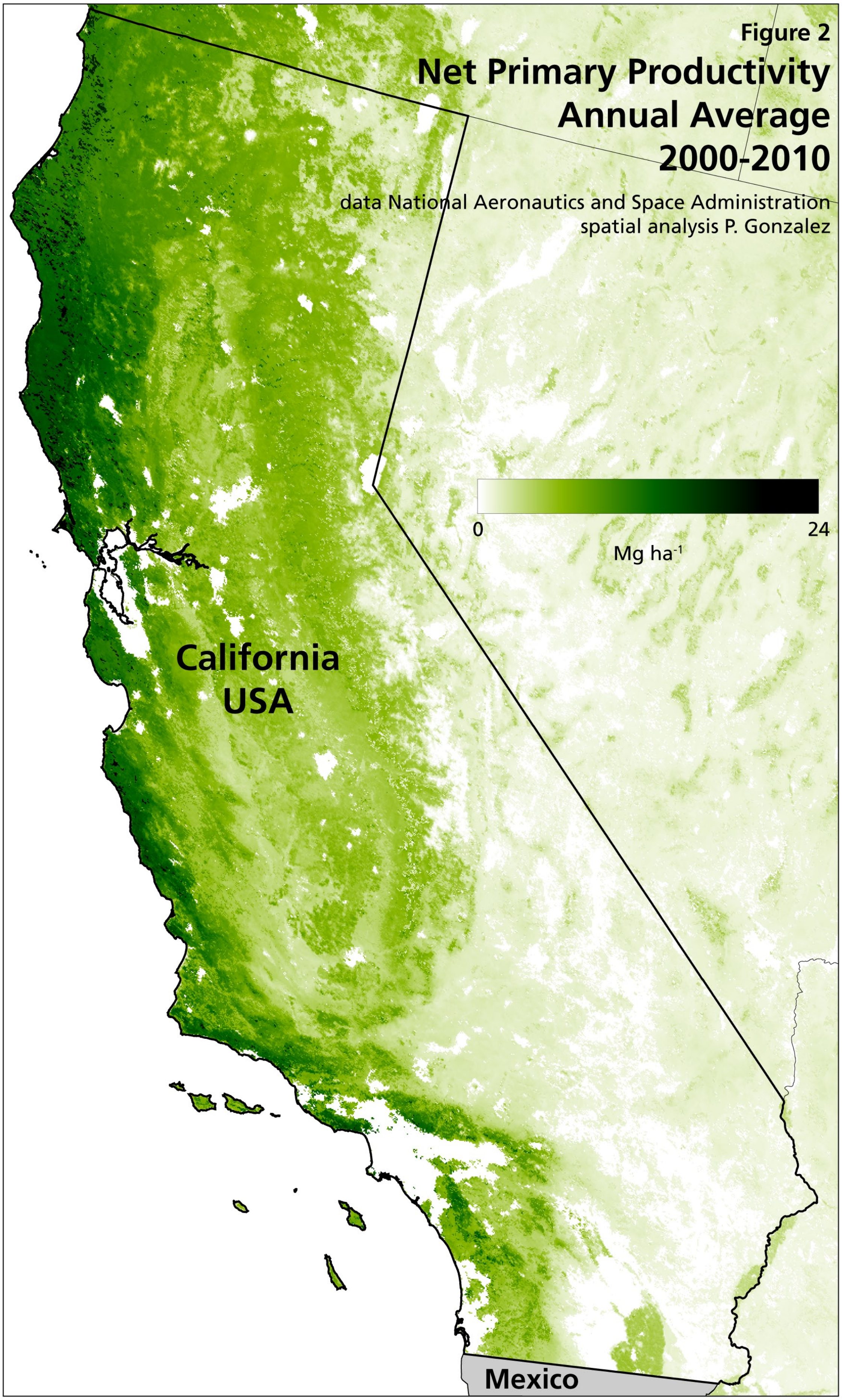
Figure 2
Net Primary Productivity
Annual Average
2000-2010
data National Aeronautics and Space Administration
spatial analysis P. Gonzalez
0
24
Mg ha-1
California
USA
Mexico

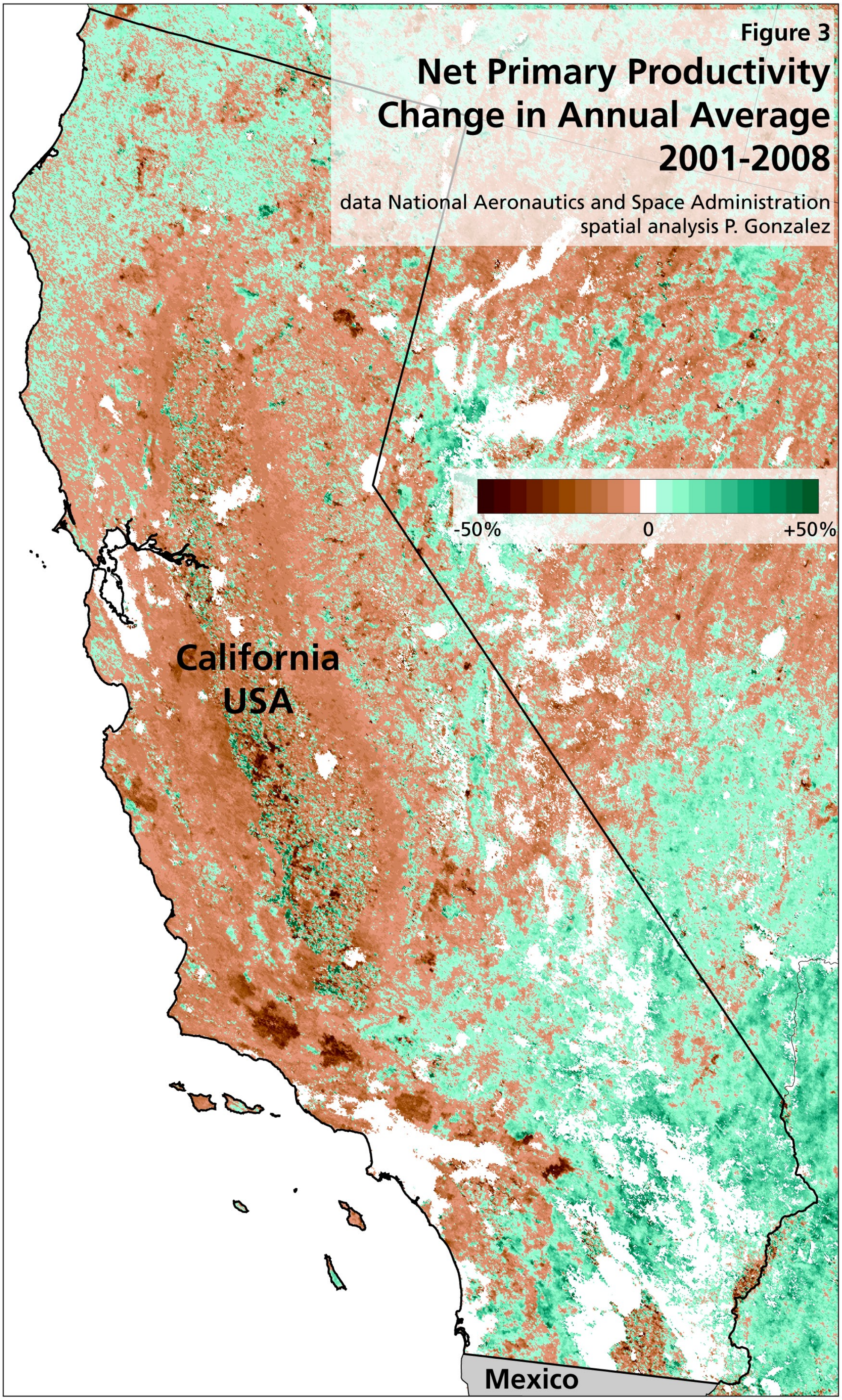

Figure 3
Net Primary Productivity
Change in Annual Average
2001-2008
data National Aeronautics and Space Administration
spatial analysis P. Gonzalez
-50%
0
+50%
California
USA
Mexico

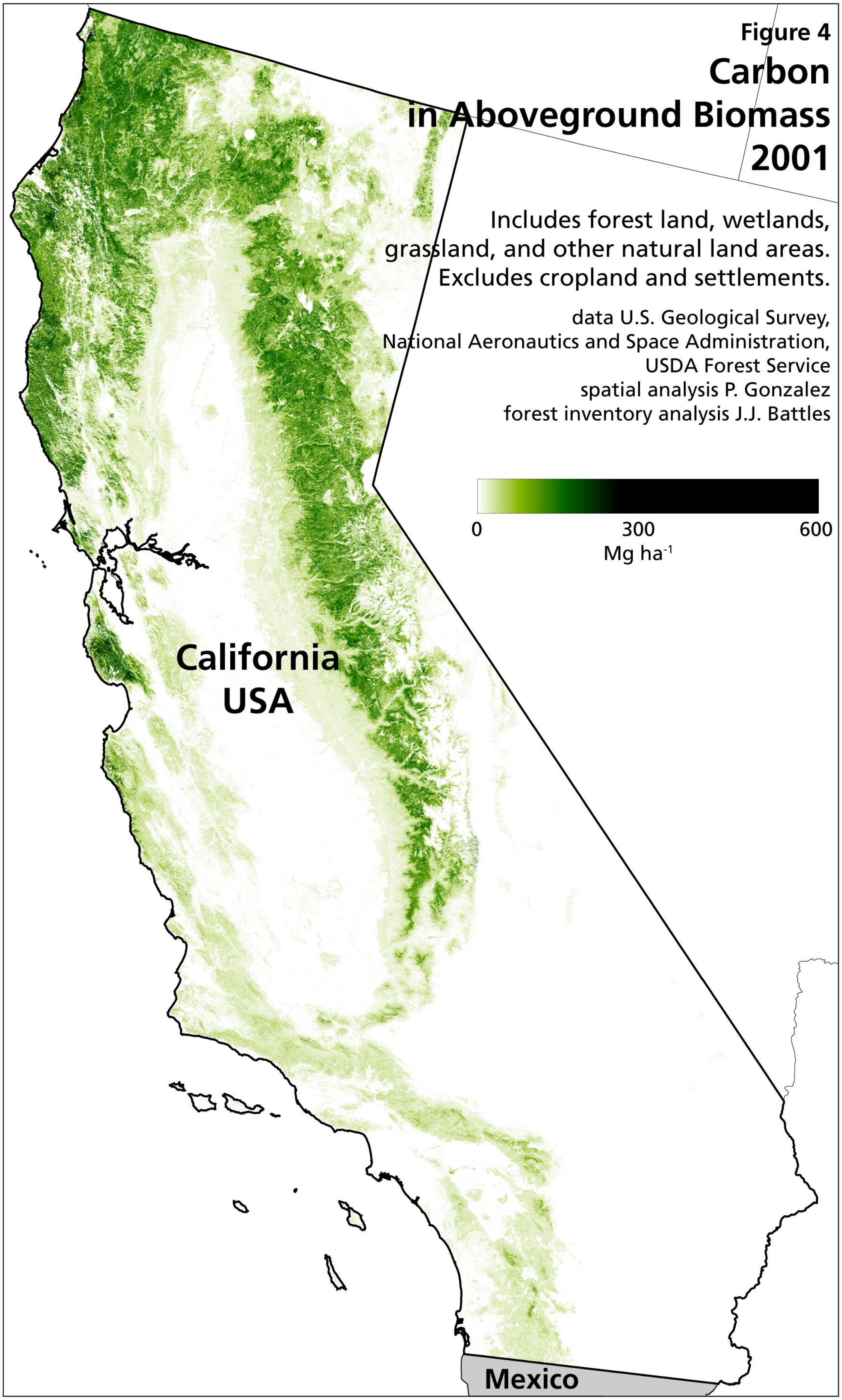

Figure 4
Carbon
in Aboveground Biomass
2001
Includes forest land, wetlands,
grassland, and other natural land areas.
Excludes cropland and settlements.
data U.S. Geological Survey,
National Aeronautics and Space Administration,
USDA Forest Service
spatial analysis P. Gonzalez
forest inventory analysis J.J. Battles
0
300
600
Mg ha-1
California
USA
Mexico

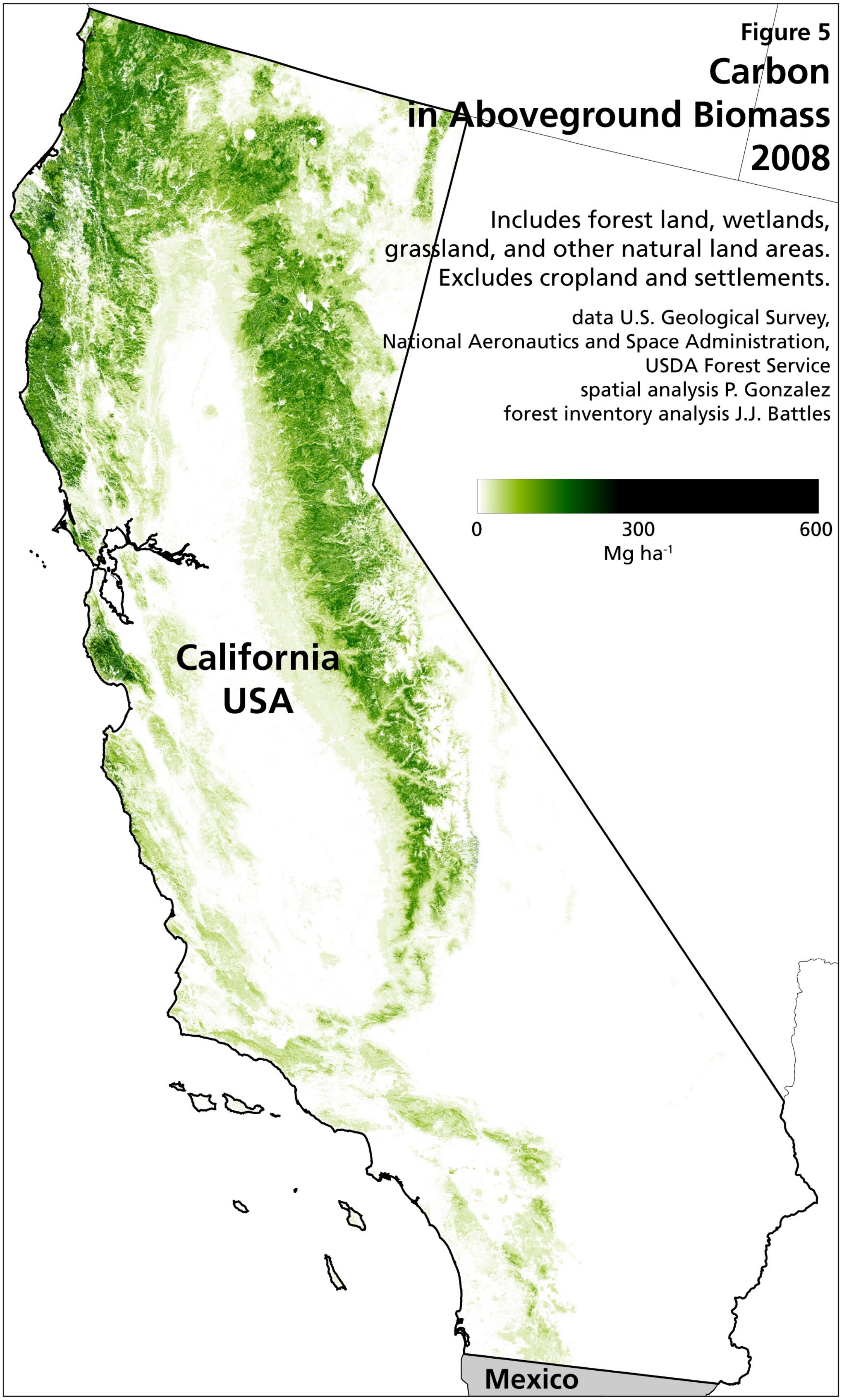
Figure 5
Carbon
in Aboveground Biomass
2008
Includes forest land, wetlands,
grassland, and other natural land areas.
Excludes cropland and settlements.
data U.S. Geological Survey,
National Aeronautics and Space Administration,
USDA Forest Service
spatial analysis P. Gonzalez
forest inventory analysis J.J. Battles
0
300
600
Mg ha-1
California
USA
Mexico

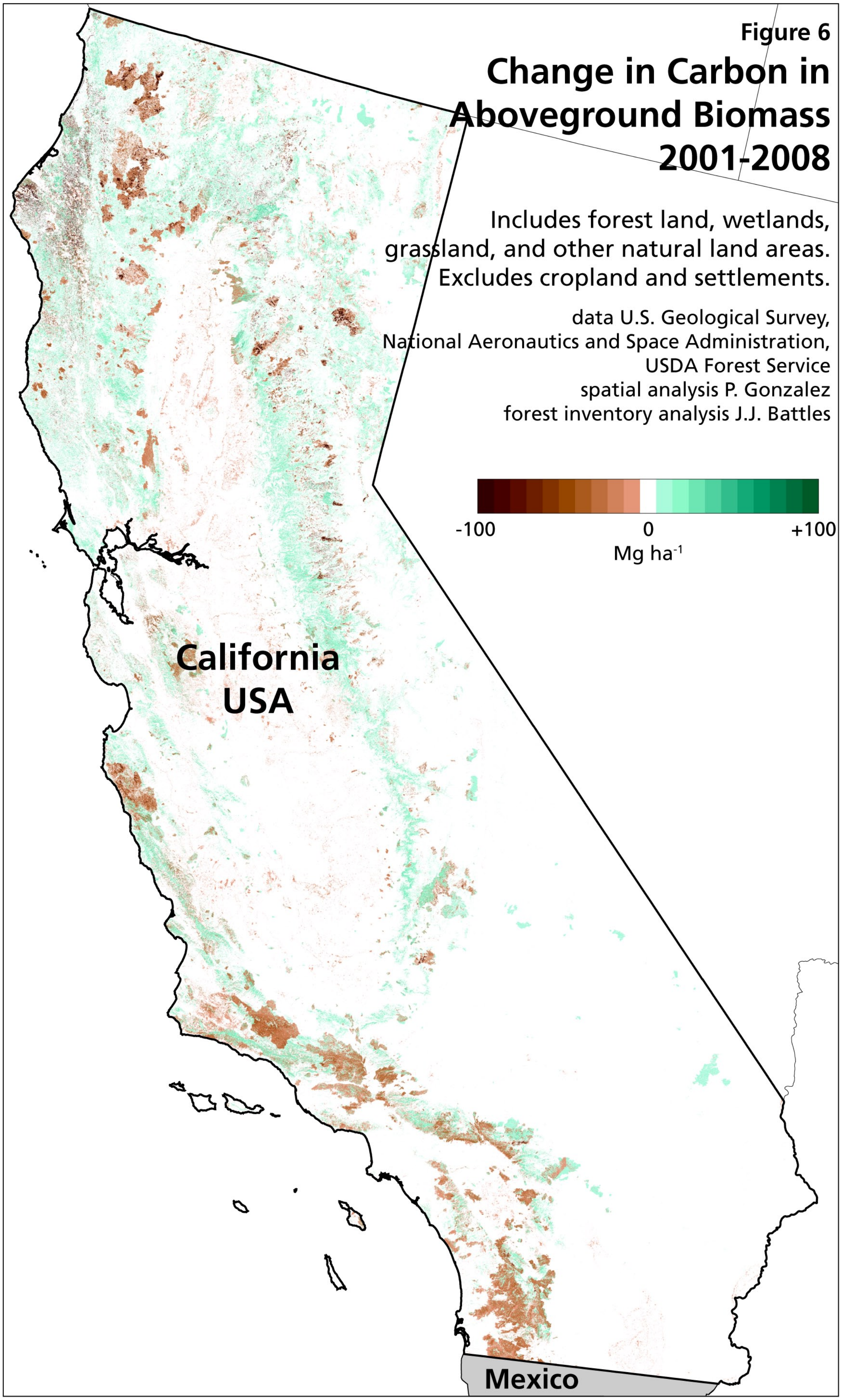
Figure 6
Change in Carbon in Aboveground Biomass 2001-2008
Includes forest land, wetlands, grassland, and other natural land areas. Excludes cropland and settlements.
data U.S. Geological Survey, National Aeronautics and Space Administration, USDA Forest Service
spatial analysis P. Gonzalez
forest inventory analysis J.J. Battles
-100
0
+100
Mg ha-1
California
USA
Mexico

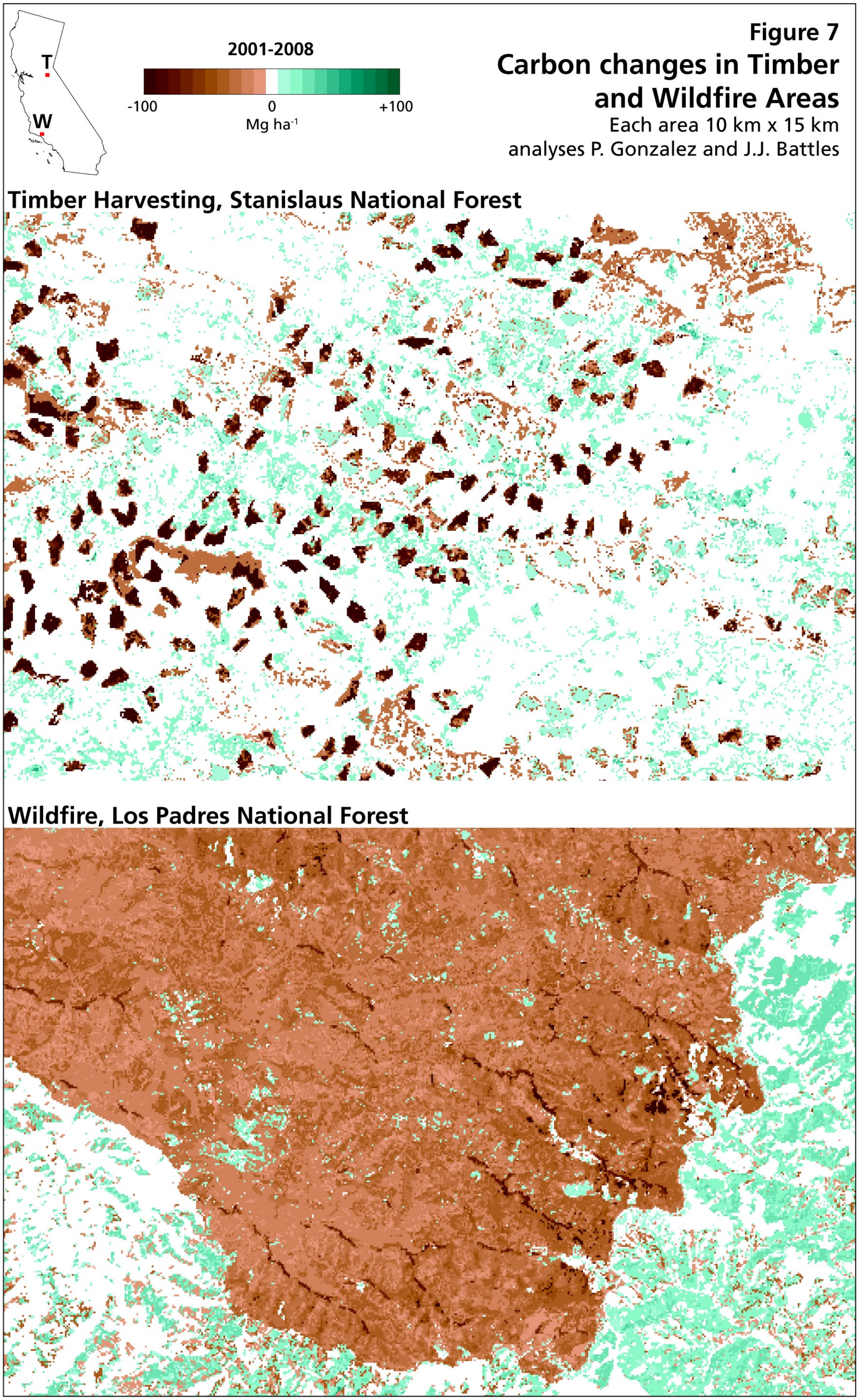

Figure 7
Carbon changes in Timber and Wildfire Areas
Each area 10 km x 15 km
analyses P. Gonzalez and J.J. Battles

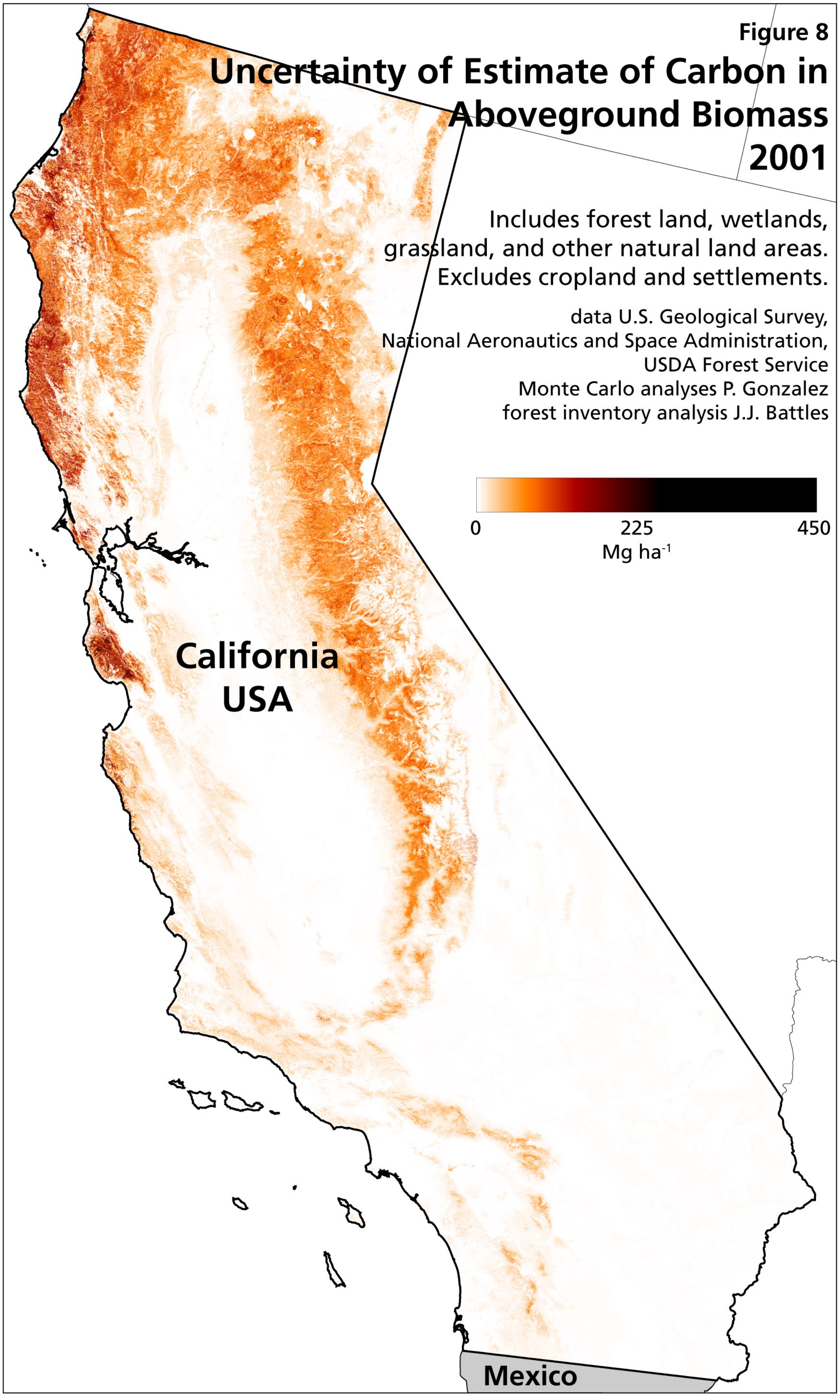
Figure 8
Uncertainty of Estimate of Carbon in Aboveground Biomass 2001
Includes forest land, wetlands, grassland, and other natural land areas. Excludes cropland and settlements.
data U.S. Geological Survey,
National Aeronautics and Space Administration,
USDA Forest Service
Monte Carlo analyses P. Gonzalez
forest inventory analysis J.J. Battles
0
225
450
Mg ha-1
California
USA
Mexico

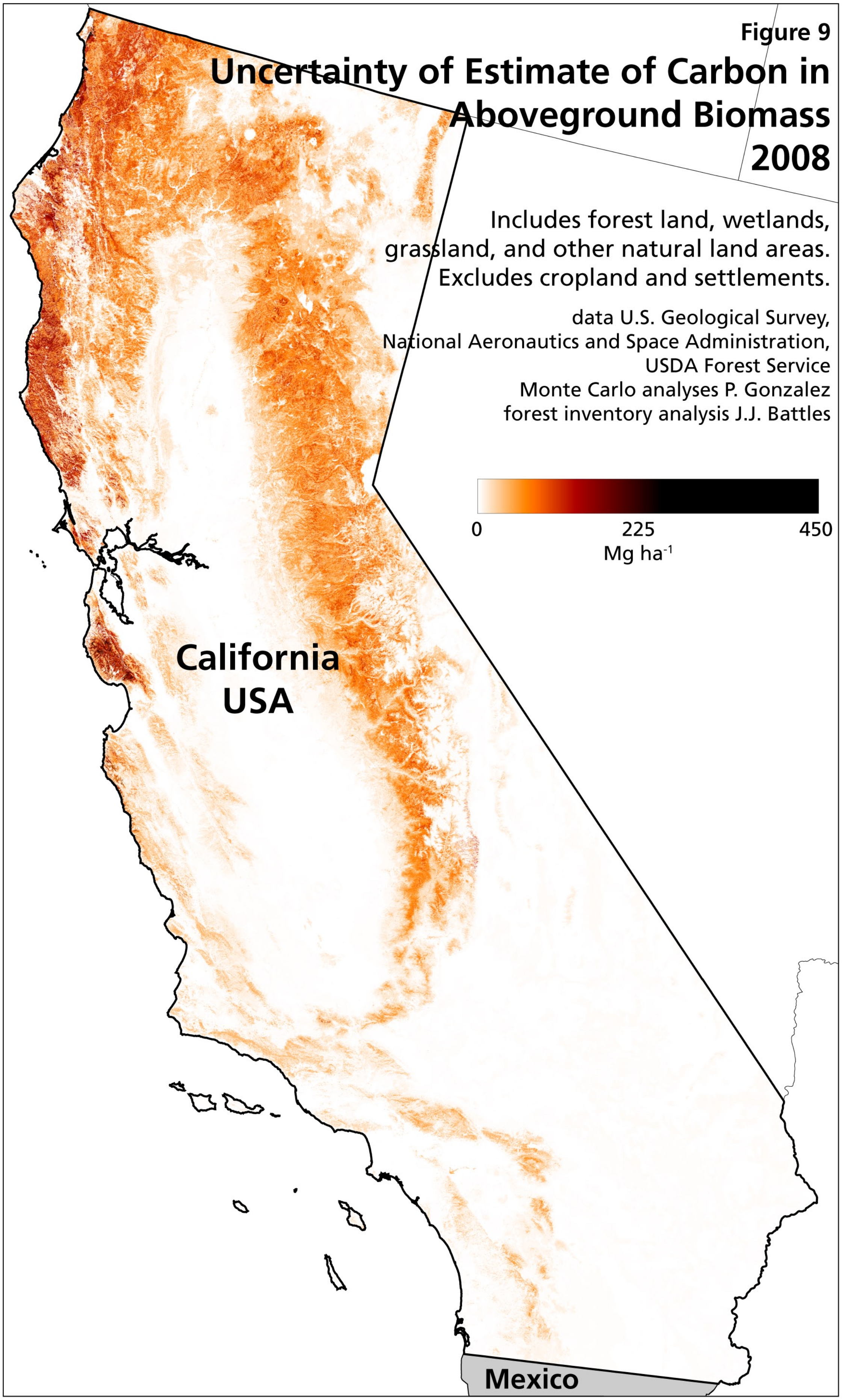
Figure 9
Uncertainty of Estimate of Carbon in Aboveground Biomass 2008
Includes forest land, wetlands, grassland, and other natural land areas. Excludes cropland and settlements.
data U.S. Geological Survey, National Aeronautics and Space Administration, USDA Forest Service
Monte Carlo analyses P. Gonzalez
forest inventory analysis J.J. Battles
0
225
450
Mg ha-1
California USA
Mexico