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Forest carbon densities and uncertainties from Lidar, QuickBird, and field measurements in California

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ABSTRACT

Greenhouse gas inventories and emissions reduction programs require robust methods to quantify carbon sequestration in forests. We compare forest carbon estimates from Light Detection and Ranging (Lidar) data and QuickBird high-resolution satellite images, calibrated and validated by field measurements of individual trees. We conducted the tests at two sites in California: (1) 59 km^2 of secondary and old-growth coast redwood (*Sequoia sempervirens*) forest (Garcia–Mailliard area) and (2) 58 km^2 of old-growth Sierra Nevada forest (North Yuba area). Regression of aboveground live tree carbon density, calculated from field measurements, against Lidar height metrics and against QuickBird-derived tree crown diameter generated equations of carbon density as a function of the remote sensing parameters. Employing Monte Carlo methods, we quantified uncertainties of forest carbon estimates from uncertainties in field measurements, remote sensing accuracy, biomass regression equations, and spatial autocorrelation. Validation of QuickBird crown diameters against field measurements of the same trees showed significant correlation ($r = 0.82$, $P < 0.05$). Comparison of stand-level Lidar height metrics with field-derived Lorey's mean height showed significant correlation (Garcia–Mailliard $r = 0.94$, $P < 0.0001$; North Yuba $R = 0.89$, $P < 0.0001$). Field measurements of five aboveground carbon pools (live trees, dead trees, shrubs, coarse woody debris, and litter) yielded aboveground carbon densities (mean ± standard error without Monte Carlo) as high as 320 ± 35 Mg ha^{-1} (old-growth coast redwood) and 510 ± 120 Mg ha^{-1} (red fir [*Abies magnifica*] forest), as great or greater than tropical rainforest. Lidar and QuickBird detected aboveground carbon in live trees, 70–97% of the total. Large sample sizes in the Monte Carlo analyses of remote sensing data generated low estimates of uncertainty. Lidar showed lower uncertainty and higher accuracy than QuickBird, due to high correlation of biomass to height and undercounting of trees by the crown detection algorithm. Lidar achieved uncertainties of <1%, providing estimates of aboveground live tree carbon density (mean ± 95% confidence interval with Monte Carlo) of 82 ± 0.7 Mg ha^{-1} in Garcia–Mailliard and 140 ± 0.9 Mg ha^{-1} in North Yuba. The method that we tested, combining field measurements, Lidar, and Monte Carlo, can produce robust wall-to-wall spatial data on forest carbon.

1. Introduction

A growing forest naturally removes greenhouse gases from the atmosphere and reduces the magnitude of global climate change. Global vegetation and soils removed carbon from the atmosphere at a rate (mean ± 66% confidence interval) of 4.7 ± 1.2 Gt y^{-1} in 2008, compared to fossil fuel emissions of 8.7 ± 0.5 Gt y^{-1} and deforestation emissions of 1.2 ± 0.7 Gt y^{-1} (Intergovernmental Panel on Climate Change [IPCC], 2007; Le Quéré et al., 2009). Parties to the United Nations Framework Convention on Climate Change (UNFCCC) and jurisdictions such as the State of California, USA, conduct national and sub-national greenhouse gas inventories. Furthermore, the UNFCCC and other institutions have established greenhouse gas emissions reduction programs with credits for forest conservation, afforestation, and reforestation. Greenhouse gas inventories and emissions reduction programs require scientifically robust methods to quantify forest carbon storage over time across extensive landscapes.

Monitoring forest carbon in forests with high spatial variation of tree density and species composition poses major challenges (Fahey

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et al., 2009). The financial cost of forest inventory can render it infeasible as the sole method for estimating the forest carbon of extensive areas. In addition, forest inventory programs that are funded sufficiently for large-scale forest carbon monitoring, such as the Forest Inventory and Analysis (FIA) program of the United States Department of Agriculture (USDA) Forest Service, use large administrative areas as units of analysis (Woodbury et al., 2007), masking local variability.

Remote sensing, calibrated by field measurements, addresses these challenges. Methods commonly calculate forest carbon as the product of surface areas of land cover types, classified by satellite systems with moderate spectral or spatial resolutions, e.g. Landsat and MODIS, and mass of carbon per unit area (carbon density), derived from field measurements of trees and allometric equations, summed over all land cover types (Achard et al., 2004; Blackard et al., 2008; DeFries et al., 2007; Potter et al., 2008; Saatchi et al., 2007). The number of land cover types that satellites with moderate spectral or spatial resolutions can accurately discriminate, generally five to twenty classes (Bartholomé & Belward, 2005; Loveland et al., 2000; Sánchez-Azofeifa et al., 2009), limits the possible carbon density of each pixel to a few discrete values.

In contrast to satellites with moderate spectral or spatial resolutions, high-resolution Lidar and high-resolution satellites such as QuickBird, IKONOS, WorldView, and GeoEye sense physical dimensions of trees to which aboveground biomass directly correlates. 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.

Field research has demonstrated the accuracy of Lidar estimates of canopy height (Andersen et al., 2006; Magnussen & Boudewyn, 1998; Næsset, 1997; 2009) and high correlation of Lidar height metrics to field-measured aboveground biomass (Boudreau et al., 2008; Drake et al., 2002; Hurtt et al., 2004; Hyde et al., 2006; Lefsky et al., 1999; 2005; Næsset & Gobakken, 2008) and forest carbon density (Balzter et al., 2007; Patenaude et al., 2004). Financial and expertise requirements of Lidar methods have prevented their widespread adoption for forest carbon monitoring in tropical countries, although it has been tested in the Brazilian Amazon (Asner, 2009). Lidar has produced more accurate estimates of forest biomass than Landsat (Lefsky et al., 2001), high spectral resolution sensors (Lefsky et al., 2001), and synthetic aperture radar (Sexton et al., 2009). Direct comparison of Lidar to high-resolution satellites for forest carbon monitoring remains an area for further investigation because these two systems are potential tools for national greenhouse gas inventories (Bickel et al., 2006) and reducing emissions from deforestation and degradation (REDD) programs (DeFries et al., 2007).

Research on high-resolution optical images from QuickBird and IKONOS has tested algorithms to detect crown diameter and other tree characteristics in a wide range of forest biomes (Asner et al., 2002; Clark et al., 2004; Palace et al., 2008; Thenkabail et al., 2004; Wulder et al., 2004). High-resolution satellites can detect individual tree crowns but the accurate monitoring of forest carbon has not been fully demonstrated.

The choice of remote sensing system will influence the levels of uncertainty in the estimates of forest carbon. To quantify uncertainty of forest carbon estimates, the IPCC (2006) recommends Monte Carlo analysis, which reduces uncertainty compared to simple combination of confidence intervals of equation variables (Mandel, 1984). Research has applied Monte Carlo analysis to forest carbon at regional (Chambers et al., 2007) and national (Monni et al., 2007) scales, although not all forest carbon studies quantify uncertainty.

We have sought to advance the application of remote sensing to forest carbon monitoring through research that provides new information on the capabilities of Lidar and high-resolution satellites, on carbon densities of high-biomass forests, and on uncertainties of forest carbon estimates. Our research objectives are: (1) to directly compare forest carbon estimates from Lidar data and QuickBird high-resolution satellite images, calibrated and validated by field measurements of individual trees, (2) to estimate forest carbon densities in two high-biomass forests in California, and (3) to quantify, with Monte Carlo analysis, uncertainties in forest carbon estimates from uncertainties in field measurements, remote sensing accuracy, biomass regression equations, and spatial autocorrelation.

2. Methods

2.1. Garcia–Mailliard research area

The Garcia–Mailliard research area (Fig. 1) consists of two separate units between 38.89° and 38.93° N and 123.32° and 123.55° W: (1) 58 km^2 eastern half of the private Garcia River forest and (2) 1 km^2 Mailliard Redwoods State Natural Reserve (SNR). Located in the North Coast Range of California, the area consists of low ridges and shallow valleys. Garcia River forest is secondary coast redwood forest with post-harvest stands approximately 20–80 years old. The California Climate Action Registry has registered a carbon project in Garcia River forest. Mailliard Redwoods SNR, established in 1945, consists of old-growth coast redwood forest, although not as tall as old-growth coast redwood forests further north in California with forest carbon

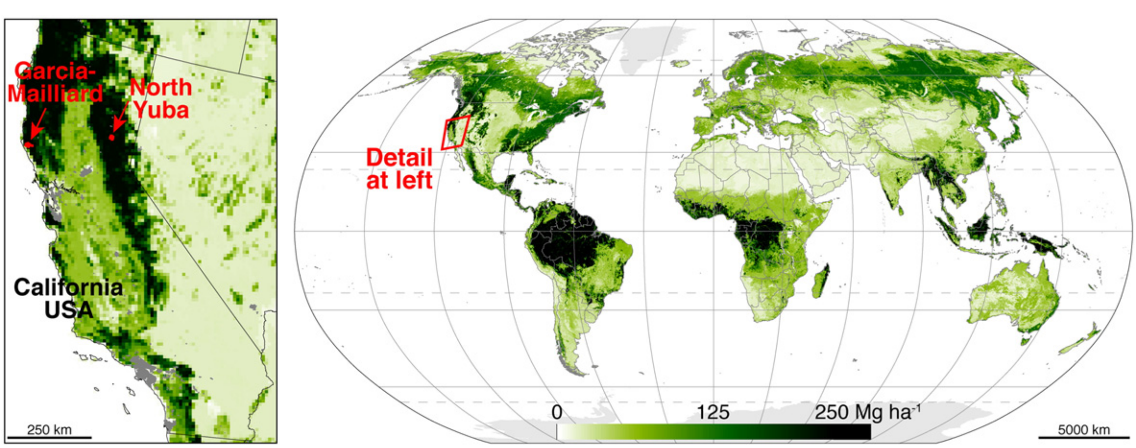

Fig. 1. Location of research areas. Background shows aboveground vegetation carbon density (Matthews et al., 2000) derived from AVHRR remote sensing (Loveland et al., 2000) and field measurements (Olson et al., 1983), analyzed at 10 km spatial resolution.