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Using Landsat-derived disturbance and recovery history and lidar to map forest biomass dynamics

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A B S T R A C T

Improved monitoring of forest biomass and biomass change is needed to quantify natural and anthropogenic effects on the terrestrial carbon cycle. Landsat's temporal and spatial coverage, moderate spatial resolution, and long history of earth observations provide a unique opportunity for characterizing vegetation changes across large areas and long time scales. However, like with other multi-spectral passive optical sensors, Landsat's relationship of single-date reflectance with forest biomass diminishes under high leaf area and complex canopy conditions. Because the condition of a forest stand at any point in time is largely determined by its disturbance and recovery history, we conceived a method that enhances Landsat's spectral relationships with biomass by including information on vegetation trends prior to the date for which estimates are desired. With recently developed algorithms that characterize trends in disturbance (e.g. year of onset, duration, and magnitude) and post-disturbance regrowth, it should now be possible to realize improved Landsat-based mapping of current biomass across large regions. Moreover, given that we now have 40 years of Landsat data, it should also be possible to use this approach to map historic biomass densities.

In this study, we developed regression tree models to predict current forest aboveground biomass (AGB) for a mixed-conifer region in eastern Oregon (USA) using Landsat-based disturbance and recovery (DR) metrics. We employed the trajectory-fitting algorithm LandTrendr to characterize DR trends from yearly Landsat time series between 1972 and 2010. The most important DR predictors of AGB were associated with magnitude of disturbance, post-disturbance condition and post-disturbance recovery, whereas time since disturbance and pre-disturbance trends showed only weak correlations with AGB. Including DR metrics substantially improved predictions of AGB (RMSE = 30.3 Mg ha^{-1}, 27%) compared to models based on only single-date reflectance (RMSE = 39.6 Mg ha^{-1}, 35%). To determine the number of years required to adequately capture the effect of DR on AGB, we explored the relationship between time-series length and model prediction accuracy. Prediction accuracy increased exponentially with increasing number of years across the entire observation period, suggesting that in this forest region the longer the historic record of disturbance and recovery metrics the more accurate the mapping of AGB. However, time series lengths of between 10 and 20 years were adequate to significantly improve model predictions, and lengths of as little as 5 years still had a meaningful impact. To test the concept of historic biomass prediction, we applied our model to Landsat time series from 1972–1993 and estimated AGB biomass change between 1993 and 2007. Our estimates compared well with historic inventory data, demonstrating that long-term Landsat observations of DR processes can aid in monitoring AGB and AGB change.

Instead of directly linking Landsat data with the limited amount of available field-based AGB data, in this study we used the field data to map AGB with airborne lidar and then sampled the lidar data for model training and error assessment. By using lidar data to build and test our prediction model, this study illustrates that lidar data have great value for scaling between field measurements and Landsat data.

1. Introduction

Improved monitoring of forest biomass is required to understand the role of forest ecosystems in the global climate and to implement national and international mitigation strategies that reduce greenhouse gas emissions (Aber et al., 2001; Bonan, 2008; Houghton, 2005). Current observations of the land–atmosphere C-flux based on measurements via eddy covariance techniques (Baldocchi, 2003) and field inventories (Goodale et al., 2002) are too sparse in time and space to allow inferences of terrestrial carbon sources and sinks with sufficient accuracy (Denman et al., 2007; Houghton, Hall, & Goetz, 2009). Consequently, the value of remote sensing data for estimating forest aboveground biomass (AGB) is high.

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The most promising strategies for improving forest carbon estimates with remote sensing data are to combine them with ecosystem process models. For example, studies have combined ecosystem process models with maps of disturbance history and age from Landsat time series (Cohen, Harmon, Wallin, & Fiorella, 1996; Masek & Collatz, 2006), and with satellite-based estimates of FPAR (fraction of photosynthetic active radiation) (Coops & Waring, 2001; Smith, Knorr, Widlowski, Pinty, & Gobron, 2008). Ecosystem models are valuable because they can provide a detailed simulation of ecophysiological processes, including those below ground, and can be run in prognostic mode, e.g. to analyze ecosystem feedbacks to future climate scenarios. However, these models also require large, detailed datasets for parameterization, and independent validation is limited. In addition, over decadal time scales, carbon fluxes are largely driven by changes in tree biomass, successional change in forest composition, and disturbance events; processes that are not well represented by current ecosystem models (Urbanski et al., 2007). Remote sensing has the potential to provide much of the detailed information that such models require.

Lidar (light detection and ranging) is currently the only sensor type whose signal does not saturate in high biomass forests (e.g. 1200 Mg ha^{-1}, Lefsky, Cohen, Parker, & Harding, 2002); thus lidar data are ideal for mapping AGB. Lidar measures the three-dimensional distribution of tree heights and foliage (Drake et al., 2002; Lefsky et al., 1999) resulting in accurate estimates of forest biomass across a broad range of forest types and biomes (Dubayah et al., 2010; Lefsky et al., 2002). Lidar systems are currently available either as wall-to-wall scanners (most operational airborne systems) or as discrete samplers with ground footprints between 10 and ~65 m in diameter (Abshire et al., 2005; Blair, Rabine, & Hofton, 1999; Nelson, Krabill, & Tonelli, 1988). Several studies have now demonstrated how to integrate large footprint lidar samplers and satellite imagery to map forest biomass over temperate (Lefsky, Turner, Guzy, & Cohen, 2005), boreal (Boudreau et al., 2008), and tropical forests (Baccini et al., 2012; Helmer, Lefsky, & Roberts, 2009; Saatchi et al., 2011). Estimating biomass with airborne laser scanning data is often more accurate (Zolkos, Goetz, & Dubayah, 2013), but the high acquisition costs and data volumes currently prohibit repeated monitoring of large areas. Thus, recent research with airborne data has increasingly focused on integrating lidar with forest inventory data in multi-stage sampling frameworks (Andersen, 2009; Gregoire et al., 2011; Stephens et al., 2012), and also with satellite imagery (Andersen, Strunk, Temesgen, Atwood, & Winterberger, 2011; Wulder & Seemann, 2003). To effectively use lidar as a sampling tool in regional vegetation studies it is of interest to examine how the choice of sampling design and sampling density can reduce uncertainties in the estimates.

Multi-spectral satellite sensors provide frequent and consistent observations of the earth's surface, and have been used extensively for monitoring vegetation characteristics across a variety of spatial and temporal scales (Cohen & Goward, 2004; Running et al., 2004). As a result, a large body of research has focused on estimating biomass directly with moderate spatial resolution (e.g. Landsat, Hall, Skakun, Arsenault, & Case, 2006; Powell et al., 2010) and coarse resolution sensor data (e.g. MODIS, Baccini, Friedl, Woodcock, & Warbington, 2004; Blackard et al., 2008). To estimate AGB, these studies often utilize empirical models based on single-date reflectance and field measurements. However, the signal recorded by passive optical multi-spectral sensors is known to saturate under closed canopy conditions (Lu, 2006) diminishing the accuracy of biomass estimates obtained from these sensors in medium to high biomass forests (e.g. > ~150 Mg ha^{-1}).

Despite this limitation, estimating AGB with multi-spectral sensors remains an active field of research. Approaches that rely solely on regional statistics and thematic land cover data may greatly misrepresent the actual spatial distribution of AGB (Goetz et al., 2009). Recently, Avitabile, Herold, Henry, and Schmullius (2011) compared available biomass maps for Uganda and found, while estimates obtained from multi-spectral data and regression models were conservative, maps based on biome-average values and national land cover data vastly overestimated AGB. To improve AGB estimates with multi-spectral data, scientists have tested a variety of modeling techniques (Hudak, Lefsky, Cohen, & Berterretche, 2002; Powell et al., 2010), utilized multiple intra-annual imagery (Lefsky, Cohen, & Spies, 2001) and inter-annual time series (Helmer et al., 2010), and included topographic and climate variables in addition to spectral variables (Baccini et al., 2004; Powell et al., 2010) with mixed success.

One potential means of enhancing the relationship between Landsat reflectance and AGB is by incorporating Landsat spectral trends of disturbance and recovery (DR) prior to the date for which predictions are desired (Pflugmacher, Cohen, & Kennedy, 2012). The conceptual basis for combining DR metrics with spectral data derives from ecological observations that type (e.g. fire, harvest, insect) and intensity of disturbances influence forest structure, composition, and carbon dynamics (Franklin et al., 2002; Halpern, 1988; Harmon, Ferrell, & Franklin, 1990; Spies, 1998). Disturbance type and severity influence the proportion of live biomass that combusts during a fire, is transferred to dead woody biomass or removed from a site as products (Kasischke et al., 2005). In combination with environmental factors, disturbances determine the rate and pathways of subsequent recovery (Gough, Vogel, Harrold, George, & Curtis, 2007; Meigs, Donato, Campbell, Martin, & Law, 2009), resulting in highly variable spatial and temporal patterns of forest regrowth (Halpern, 1988; Yang, Cohen, & Harmon, 2005).

Recently, we tested the DR approach for predicting AGB with good success (Pflugmacher et al., 2012). Including DR metrics calculated from yearly Landsat time series (1972–2010) into empirical models improved prediction accuracy substantially; root mean square error (RMSE) decreased from 57% to 41% compared to models that used only single-date (SD) Landsat data. However, the study was a proof-of-concept and limited to 51 field plots and manually-digitized trajectories. Here, our objective was to extend that work to map AGB and AGB change (ΔAGB). Accomplishing this required that we: 1) automate the characterization of DR metrics, 2) develop DR-based AGB models, 3) and test if those models can be used to predict historic AGB and ΔAGB. Further, we wanted to explore the use of airborne lidar for training statistical models that are better representative of the wide range of forests and disturbance regimes in the study area than were a limited sample of field measurements. Thus, instead of using the field plots from our previous study directly for model training, we use these plots to create a high-resolution AGB surface predicted from airborne lidar data. We then sample the lidar-based AGB predictions and quantify the effect of sampling density on the prediction accuracy of the DR models.

2. Methods

2.1. Study area

The study area is located in the Blue Mountains of eastern Oregon, USA (Fig. 1). The area is ~830 km^2 and covers two large watersheds of the Upper Middle Fork John Day River. Current forest structure has been shaped by natural and anthropogenic disturbances, with harvest, insects, and fire as major agents. Mountain pine beetle (*Dendroctonus ponderosae* Hopkins) and western spruce budworm (*Choristoneura occidentalis* Freeman) are the main causes of tree mortality and defoliation (Meigs, Kennedy, & Cohen, 2011). Thinning harvest and frequent low intensity fire are common, which have created structurally and compositionally complex mixed and multi-aged conifer-dominated forests (Campbell & Liegel, 1996). Two high intensity wildfires have been documented by the Monitoring Trends in Burn Severity (MTBS) project (http://www.mtbs.gov/). The larger fire burned approximately 14,800 ha in 1996 in the northern part, and the smaller fire burned in 2002 approximately 2600 ha in the south east part of the study area.

The Blue Mountain region is characterized by a dry climate, with average annual precipitation from 305 mm to 1270 mm. Elevation ranges