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Airborne laser scanner-assisted estimation of aboveground biomass change in a temperate oak–pine forest

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ABSTRACT

We estimated aboveground tree biomass and change in aboveground tree biomass using repeated airborne laser scanner (ALS) acquisitions and temporally coincident ground observations of forest biomass, for a relatively undisturbed period (2004–2007; Δ_{07-04}), a contrasting period of disturbance (2007–2009; Δ_{09-07}), and an integrated period (2004–2009; Δ_{09-04}). A simple random sampling (SRS) estimator was used to estimate means and variances of biomass and biomass change for each measurement occasion and interval. For each year, linear regression models were used to predict mean total aboveground tree biomass for live, dead, and total biomass components from ALS-derived variables. These models predicted biomass with $R^2 = 0.68$, 0.59, and 0.70 and RMSEs of 32.7, 30.5, and 31.7 Mg ha^{-1} for 2004, 2007 and 2009, respectively. A model assisted indirect estimator was then used to estimate biomass and biomass change for comparison to the field-based SRS estimator. This model assisted indirect approach decreased standard errors of biomass estimation relative to the SRS estimator, but had larger variances for biomass change estimation. Linear regression models were also used to directly predict field-estimated biomass change using ALS Δ-variables, calculated as the difference between multi-temporal ALS variables, for the study area. Integrated over the 6 year period, these change models had $R^2 = 0.81$, 0.72, and 0.68 with RMSEs of 2.0, 9.3, and 1.0 Mg ha^{-1} yr^{-1} for live, dead, and total aboveground tree biomass, respectively. A model assisted direct estimator reduced standard errors of change estimates by 100–200% compared to the field-based estimates. We discuss several potential advantages and limitations of the direct and indirect approaches. Our primary finding is that model assisted direct estimation of biomass change decreased estimation uncertainty relative to both field and model assisted indirect estimation.

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1. Introduction

There is large uncertainty in the carbon sink strength of terrestrial ecosystems, recently estimated at 1.1 ± 0.8 Pg C yr^{-1} globally (Pan et al., 2011). In response, several international initiatives are aimed at increasing the precision of forest biomass and estimates of biomass change at multiple spatial and temporal scales. These include, but are not limited to, the United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (UN-REDD; http://www.un-redd.org), the Kyoto Protocol's Land Use, Land Use Change and Forestry section (IPCC, 2006) and the North American Carbon Program (NACP; http://www.nacarbon.org/nacp). These initiatives have brought into focus the need for repeatable, cost-effective, and simple remote sensing methodologies for monitoring, reporting, and verification (MRV) of biomass stocks (Goetz & Dubayah, 2011).

The estimation of change in biomass stocks is an area of particular interest (Houghton, Hall, & Goetz, 2009). Because of strong interest in the net exchange of CO_2 between the land and the atmosphere, it may be more important that we understand the trajectory of the global carbon storage than to accurately estimate the storage itself. The estimation of biomass loss and accumulation through time as a response to various disturbance events presents methodological challenges, particularly at larger spatial scales (Goetz et al., 2012). Disturbances such as wildfire, hurricanes, and insect invasions impact both standing biomass and the future rates of change in these pools. Spatially, we have been able to incorporate time-series spatial reflectance data to illustrate the extent and patterning of disturbance at high temporal resolution (e.g., Zhu, Woodcock, & Olofsson, 2012) and broad spatial scales (e.g., Blackard et al., 2008; Masek et al., 2008). Many studies have demonstrated, under some conditions, the ability of spatial reflectance data to reflect the severity of disturbance, particularly in the realm of wildland fire intensity (e.g., Keeley, 2009; Veraverbeke & Hook, 2013).

The application of Light Detection and Ranging (LiDAR) data to the problem of mapping and estimation of terrestrial biomass has been shown to greatly increase the spatial resolution and accuracy of aboveground biomass estimates in many studies (see Asner et al., 2010, 2011;

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Zolkos, Goetz, & Dubayah, 2013). Several recent studies have incorporated more thorough statistical techniques to estimate the uncertainty of various biomass estimators across landscapes (Mascaro, Detto, Asner, & Muller-Landau, 2011; Næsset et al. 2011), with one example reporting uncertainty at < 1% (standard error of the mean; SE) of the estimated landscape-scale mean carbon density (Gonzalez et al., 2010). Several studies have successfully decreased estimation uncertainty while maximizing cost-effectiveness by targeting airborne laser scanner (ALS) data collections to sample small portions of the population, rather than gathering wall to wall data (e.g., Andersen, Strunk, Temesgen, Atwood, & Winterberger, 2012, Gobakken et al., 2012). This work has been complemented by additional simulation studies that were designed to optimize sampling designs in ways that maximized sampling efficiency while minimizing estimation uncertainty (Ene et al., 2012, 2013).

The characterization of change using multi-date ALS acquisitions has not received the same attention as single-date characterization because of the overall paucity of these repeated-measure datasets. However, as multi-temporal datasets have become available, several studies have demonstrated the utility of this approach. For example, Solberg, Næsset, Hanssen, and Christiansen (2006) illustrated the use of repeated ALS acquisitions to detect changes in LAI during an insect attack on Scots pine (*Pinus sylvestris* L.) in Norway. Additional research has documented canopy gap formation and closure over two time periods (Vepakomma, St-Onge, & Keenshaw, 2008, 2011). The estimation of individual stem height growth has also been reported in several studies (Yu, Hyyppä, Kaartinen, & Maltamo, 2004; Yu et al., 2005; Yu, Hyyppä, Kukko, Maltamo, & Kaartinen, 2006). Additionally, Næsset and Gobakken (2005), Hopkinson, Chasmer, and Hall (2008), and Yu, Hyyppä, Kaartinen, Maltamo, and Hyyppä (2008) reported that they were able to estimate mean height and volume change at the plot level, albeit with low precision.

Even fewer studies have addressed the efficacy of using multi-date LiDAR acquisitions for the estimation of biomass change. Dubayah et al. (2010) used large-footprint airborne LiDAR data (LVIS) to estimate forest structure and biomass change at 1 ha resolution at La Selva Biological Station, Costa Rica. They reported success at estimating change in younger forest areas, but were not able to discern increment in older stands. Hudak et al. (2012) employed multi-date ALS acquisitions to estimate biomass changes in an actively-managed forest landscape and concluded that their methodology of modeling biomass separately for two ALS acquisitions and differencing the resultant model outputs yielded estimates of biomass change that could be used to monitor biomass change and carbon flux across large tracts of land. Both Næsset, Bollandsås, Gobakken, Gregoire, and Ståhl (2013) and Bollandsås, Gregoire, Næsset, and Øyen (2013) employed a similar indirect estimation technique as Hudak et al. (2012), and also directly modeled the change in biomass using corresponding change in predictor variables (Δ-variables) derived from the ALS datasets. Bollandsås et al. (2013) indicated that this direct prediction methodology produced smaller residuals and RMSEs than the indirect approach. Næsset et al. (2013) also indicated a smaller standard error of the landscape mean biomass change using a similar direct modeling and estimation approach.

The potential for using ALS as an auxiliary dataset for improving estimates of forest attribute change is exciting in many fields. Of particular interest is the estimation of changes to these attributes following disturbance events such as wildfire, insect defoliation, or blowdown events. Linking spatially explicit estimates of attribute change with stratification schemes would allow for categorical assessment of these events, thereby increasing reporting precision and contributing to the analysis of events that may be spatially complex and thus difficult to capture with traditional field inventories. However, the paucity of repeated ALS datasets and the scarcity of appropriately re-measured inventory data within their bounds have limited the study and application of ALS-based change estimation. Thus, fundamental studies are necessary to develop a knowledge base that builds towards estimating complex biomass changes with improved estimation uncertainties.

Our study aims to estimate aboveground biomass change for disturbed and undisturbed time periods using multitemporal ALS datasets. Specifically, our objective was to compare the effectiveness of model-assisted direct and indirect approaches for estimating biomass and biomass change over a 3 × 3 km area using three repeated ALS datasets as auxiliary data. The repeated ALS acquisitions allowed us to compare estimates developed over two contrasting time periods. The first time period (3 years) had little field observed mortality while the second period (2 years) included extensive, heterogeneous, stem mortality following Gypsy moth (*Lymantria dispar*) defoliation. We also integrated both time periods for a 5-year analysis of biomass change. We explored three techniques for the estimation of biomass change. As the first method, we used a field-based simple random sampling estimator of aboveground biomass change. We then used linear regression models to predict biomass across the study area for each of the three ALS acquisitions. The second method indirectly estimated mean biomass change by differencing estimates of biomass for two measurement occasions. The third method used models to directly predict the change in biomass over three time periods in response to corresponding changes in ALS predictor variables. These predictions were then used to directly estimate mean biomass change across the study area. While primarily focused on comparing approaches for change estimation, this work also provides analysis that informs several other knowledge gaps. For instance, there is no literature currently available that demonstrates and evaluates the efficacy of using repeated ALS datasets to estimate biomass change on the Atlantic Coastal Plain of the United States. Additionally, there are few studies that provide estimates of biomass change before and after heterogeneous, non-stand replacing disturbance events.

2. Data

The study site is located in Burlington County, New Jersey, USA, within the Pinelands Management Area (PMA), a UNESCO MAB reserve site (Fig. 1; Latitude 39° 54′ 58.70″ N, Longitude 74° 35′ 51.38″ W). The study area is 3 × 3 km centered on an eddy-covariance and meteorological tower at the Silas Little Experimental Forest (SLEF) in New Lisbon, NJ (Fig. 1). The vegetation within the spatial extent of the site is composed of a predominantly oak (*Quercus* spp.) overstory with some pitch (*Pinus rigida* L.) and shortleaf pines (*Pinus echinata* Mill.). The understory is dense, and consists mostly of oak and pine saplings, scrub oaks, and shrubs, primarily huckleberry (*Gaylussacia* spp.) and blueberry (*Vaccinium* spp.). Much of the study area experienced defoliation by Gypsy moth over three years, beginning in 2006. The intensity of this disturbance was uneven and caused a spatially variable amount of stem mortality of mature oaks through the course of the study (see Clark, Skowronski, Gallagher, Renninger, & Schäfer, 2012; Clark, Skowronski, & Hom, 2010).

2.1. Field data

We installed 16 forest survey plots, patterned after the United States Department of Agriculture, Forest Service, Forest Inventory and Analysis (FIA) plot protocol (http://www.fia.fs.fed.us/), in a regular 4 by 4 pattern following the NACP Tier 3 plot design (Fig. 1; Hollinger, 2008). Each plot consisted of four circular 14.6 m diameter subplots (0.07 ha), with one subplot located in the center and three equidistant subplots distributed symmetrically around and located 36.6 m from the center subplot. 63 sub-plots were available for analysis following the rejection of a plot that was partially located on a non-forested area. Subplot centers were spatially recorded using a differentially corrected GPS (Pathfinder ProXT, Model # 52240-20, Trimble Navigation Limited, Sunnydale, CA). We made use of variables from the 63 subplots, as opposed to the 16 aggregated plots, to increase the number of data points available for biomass and biomass change predictive model fitting. This design is somewhat problematic because of the potential for spatial correlation between observations, given their