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Utility of multitemporal lidar for forest and carbon monitoring: Tree growth, biomass dynamics, and carbon flux

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ABSTRACT

Lidar transforms how we map ecosystems, but its prospect for measuring ecosystem dynamics is limited by practical factors, such as variation in lidar acquisition and lack of ground data. To address practical use of multitemporal lidar for forest and carbon monitoring, we conducted airborne lidar surveys four times from 2002 to 2012 over a region in Scotland, and combined the repeat lidar data with field inventories to map tree growth, biomass dynamics, and carbon change. Our analyses emphasized both individual tree detection and area-based, grid-level approaches. Lidar-detected heights of individual trees correlated well with field values, but with noticeable underestimation biases ($r = 0.94$, bias $= -1.5$ m, $n = 598$) due to the increased probability of missing treetops as pulse density decreases. If not corrected for such biases, lidar provided unrealistic or wrong estimates of tree growth unless laser sampling rates were high enough (e.g., > 7 points/m^2). Upon correction, lidar could detect sub-annual tree growth (p-value < 0.05). At grid levels, forest biomass density was reliably estimated from area-based lidar metrics by both Random Forests (RF) and a linear functional model ($r > 0.86$, RMSEcv < 21 Mg/ha), irrespective of laser sampling rates. But RF constantly overfit the data, often with poorer predictions. The better generality of the linear model was further confirmed by its transferability—fitted for one year but applicable to other years—a strength not possessed by RF but desired to alleviate the reliance on ground biomass data for model calibration. Resultant lidar maps of forest structure captured canopy dynamics and carbon flux at fine scales, consistent with growth histories and known disturbances. The entire 20-km^2 study area sequestered carbon at a rate of 0.59 ± 0.4 Mg C/ha/year. Overall, our study describes robust techniques well suited for multitemporal lidar analysis and affirms the utility and potential of repeat lidar data for resource monitoring and carbon management; however, the full potential cannot be attained without the support of accompanying field surveys or modeling efforts in enhancing stakeholders' trustworthiness of lidar-based inference.

1. Introduction

Forests supply timber, shelter wildlife, store carbon, and regulate climate, among others (Bonan, 2008; Zhao and Jackson, 2014). Managing forests to sustain their benefits requires effective tools to monitor landscapes over time. Ground-based tools are valuable but with limited spatial footprints (West and West, 2009). This limitation has been addressed with the use of remote sensing, especially in meeting the growing demands for spatially-explicit forest maps to track forest loss and degradation and quantify terrestrial carbon pools (Goetz et al., 2015). Of current mapping technologies, airborne lidar features prominently, due to its superior ability to resolve 3D vegetation structure (Vierling et al., 2008). Since its advent, lidar has been often acclaimed as a breakthrough in the field of vegetation remote sensing (Babcock et al., 2015; Dubayah and Drake, 2000).

Over 50 years of research has demonstrated the utility of airborne lidar for natural resource assessment (Nelson, 2013). Existing lidar systems vary in laser type, footprint, data-recording, spectral specification, or operation mode (García et al., 2012; Shan and Toth, 2008). Our focus here is a most common system: small-footprint discrete-return single-band analog laser scanners (i.e., airborne laser scanning) or simply, airborne lidar. Empirical evidence continues to proliferate to prove the exceptional value of airborne lidar for measuring forest attributes and ecosystem structure with accuracies unattainable by its

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conventional counterparts (Coomes et al., 2017; García et al., 2015; Mutlu et al., 2008; Véga et al., 2016). Given its proven capabilities, the use of airborne lidar for 3D mapping is increasing rapidly around the world (Goetz et al., 2010; Zolkos et al., 2013). Many countries, such as Denmark, Finland, and Spain, even have national-level data acquisitions completed or in progress (Stoker et al., 2008), some of which are repeat surveys.

Increased use and availability of lidar data provide opportunities to measure and study ecosystem dynamics over time (Dubayah et al., 2010; Réjou-Méchain et al., 2015). This prospect is further boosted as lidar data costs are declining, data processing is becoming more standardized, and the lidar user base is expanding (Schimel et al., 2015; Stoker et al., 2008). Accompanying the prospect are also the increasing demands for high-resolution ecosystem dynamics products to address existing environmental challenges and emerging ecological questions (Asner et al., 2013; Ma et al., 2017). Current endeavors to map landscape dynamics are still dominated by the use of multi-date satellite imagery (DeVries et al., 2015)—an area that will benefit considerably from the use of multitemporal lidar. For instance, both satellites and airborne lidar have been emphasized as essential elements of carbon monitoring systems to measure, report, and verify carbon stocks and dynamics in support of REDD+ programs and forestry-based climate policies (Goetz et al., 2015).

Despite the widely envisioned potential of multitemporal lidar, practical implementations of lidar-assisted monitoring frameworks are limited (Dassot et al., 2011; Gatziolis et al., 2010; Srinivasan et al., 2014), urging for more case studies to exemplify multitemporal lidar analysis at multiple spatial scales for diverse forest types and conditions. Prior lidar vegetation studies focused mostly on a single time at a single scale, with only a limited number of lidar change studies (Ståhl et al., 2014). Cao et al. (2016), for example, identified only seven recent airborne lidar studies on biomass dynamics, all of which considered merely two points in time at grid/plot levels (e.g., Andersen et al., 2014; Hudak et al., 2012). Still, the use of repeat lidar data for tracking ecosystem changes across scales and beyond bi-temporal analyses is examined inadequately. Such multitemporal analyses seem to be simple extensions from single-time studies, but the extensions are not always straightforward with additional challenges involved, as highlighted next.

Effective use of multitemporal lidar data is affected by many practical factors, such as availability of ancillary ground data, variation in lidar acquisition, and choice of lidar analysis methods (Næsset, 2009; Zhao et al., 2011). Most area-based vegetation attributes, such as biomass and carbon density, cannot be measured by lidar directly. Instead, they are estimated from lidar metrics at grid cells empirically via correlative models, requiring paired ground-lidar data for model calibration (Næsset et al., 2005). This paradigm is typical of remote sensing retrievals of biophysical variables and is known to have issues with model generality and transferability: Models calibrated for one scenario—a given time, sensor, region, or modeler—are not applicable to another (Foody et al., 2003; Liang, 2007). Without spatially- and temporally-coincident ground data, calibration of lidar data is infeasible. This is particularly problematic for applications with historical lidar data where temporally-coincident ground data were not collected. Moreover, lidar technologies have been improving rapidly, and most repeat lidar data were acquired differently, for example, in terms of sensor, sampling rate, flight pattern, and collection date (Cao et al., 2016; Shan and Toth, 2008). Such inconsistencies further complicate multitemporal lidar analyses (Hirata, 2004; Næsset, 2009).

In addition to area-based vegetation analysis at grid levels, the ability of lidar to detect single trees is well documented (Li et al., 2012; Nunes et al., 2017; Popescu et al., 2003; Yu et al., 2006). Trees are often delineated using heuristic algorithms such as watershed segmentation and maximum filter (Zhao and Popescu, 2007). The algorithms vary in complexity but generally involve little or no use of ancillary ground data. Therefore, individual tree analyses have been believed to suffer less from those factors limiting grid-level analyses (Li et al., 2012). However, tree parameters obtained directly by lidar are distorted versions of true values. An example is the under-estimation of actual tree height, especially at lower laser pulse rates (Hirata, 2004; Popescu et al., 2003). Thus, these direct measurements still need to be corrected empirically. Some tree parameters, such as diameter, biomass, and age, cannot be directly measured by lidar and also need to be estimated empirically (Yu et al., 2011). As in grid-level analyses, individual tree analyses should also account for the many practical limiting factors, such as lack of ground data and varying lidar specifications. To date, lidar detection of individual tree growth over time remains largely unexplored.

This study aims to assess the utility of multitemporal lidar for tracking forest and carbon dynamics and tackle practical difficulties limiting the use of historical repeat lidar data for vegetation analysis. An emphasis is on evaluating and improving multitemporal lidar methods to measure forest changes over time at both individual tree and grid levels, including tree growth, canopy dynamics, biomass change, and carbon flux. We conducted four lidar surveys in 2002, 2006, 2008, and 2012, respectively, over a Scottish forest, collected field inventory data in 2002 and 2006, combined the data to quantify forest changes at either individual tree or grid levels, and more important, evaluated alternative modeling strategies to estimate biomass and carbon stock over time, especially if lacking temporally-concomitant ancillary data to calibrate lidar biomass models. Our analyses and results confirm the power of lidar for tracking forest changes and help to advance and encourage future use of repeat lidar for carbon monitoring and ecosystem dynamics studies.

2. Study area and data

Our study area is a 20 km^2 forested landscape near the Aberfoyle village (56°10′ N, 4°22′ W) in Scotland, UK (Fig. 1a). Part of the area falls within Queen Elizabeth Forest Park. Most of the area is covered with plantations, grown and clearfelled in 40 to 60 years' rotations, but ~10% of the forests are left to transition to a continuous cover forestry system. Forest stands are dominated by Sitka spruce (*Picea sitchensis* Bong. Carr), followed by other species such as European larch (*Larix decidua*), Norway spruce (*Picea abies* H. Karst), and Lodgepole pine (*Pinus contorta* Douglas). The area is characterized by a gentle topography. Windstorms are common in this region, with gusts peaking at 150 km/h and catastrophic wind events returning every 10 to 15 years.

Four airborne lidar datasets were collected for the study area over a ten-year span using Optech's ALTM sensors (Fig. 1b). The exact acquisition years are 2002, 2006, 2008, and 2012. Although similar sensors were deployed, the acquisition specifications of the four surveys differ from each other in terms of collection month, pulse repeat frequency, flying altitude, or sampling rate (Table 1). All the lidar surveys acquired both first and last returns. The 2006 data have the highest sampling intensity with an average point density of 23.7/m^2, followed by 8.1 for 2012, 6.1 for 2002, and 3.0 for 2008. Raw data were delivered by vendors as 3D discrete-return point clouds. Each return is also tagged with echo intensity, but only the xyz ranging data were considered for our analyses.

Field inventory data were first collected in 2002 on twelve 50 m × 50 m plots and again in 2006 on the same plots (Fig. 1a): no resurvey data for 2008 and 2012. Both field surveys were conducted shortly after the respective lidar flights to reduce temporal discrepancies. Established in 2002, the 12 plots were located across the region to capture the range of canopy variability (Fig. 1a). For ease of re-survey in 2006, four corners of each plot were marked with permanent posts and trees were numbered with metal tags. Tree parameters measured include dbh, height, crown width, and tree location. Dbh was tallied for all trees of > 7 cm in diameter. Tree height was measured with a Sonic Vertex III hypsometer for all trees in three 10 × 10 m^2 subplots selected inside each 50 m × 50 m plot as well as