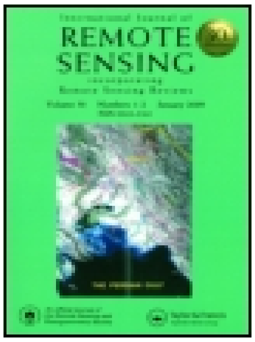

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An approach to estimating forest biomass change over a coniferous forest landscape based on tree-level analysis from repeated lidar surveys

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ABSTRACT

Forests represent a significant opportunity for carbon sequestration, but quantifying biomass change at the landscape scale and larger remains a challenge. Here we develop an approach based on repeated tree-level analysis using high-resolution airborne lidar (around 8 pulses/m^2). The study area was 53 km^2 of actively managed coniferous forestland in the Coast Range Mountains in western Oregon. The study interval was 2006–2012. Tree heights and crown areas were determined from the lidar data using point cloud clustering. Biomass per tree was estimated with allometry. Tree-level data (N = 14,709) from local USDA Forest Service Forest Inventory and Analysis plots provided the basis for the allometry. Estimated biomass change over the 6-year interval averaged −1.3 kg m^{-2} year^{-1}, with the average gain in undisturbed areas of 1.0 kg m^{-2} year^{-1}. Full harvest occurred on 3% of the area per year. For surviving trees, the mean change in height was 0.5 m year^{-1} (SD = 0.3) and the mean change in biomass was 45.3 kg year^{-1} (SD = 6.7). The maximum bin-average increase in biomass per tree (57.3 kg year^{-1}) was observed in trees of intermediate height (35–40 m). In addition to high spatially resolved tracking of forest biomass change, potential applications of repeated tree-level surveys include analysis of mortality. In this relatively productive forest landscape, an interval of 6 years between lidar acquisitions was adequate to resolve significant changes in tree height and area-wide biomass.

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1. Introduction

Changes in forest biomass play a significant role in the global carbon cycle (Pan et al. 2011), and are of interest in relation to climate change mitigation (UNFCCC 2008). Approaches to quantifying changes in forest biomass include traditional repeated plot-based inventories (Gray and Whittier 2014), but remote sensing offers the opportunity for continuous coverage over large domains, which can reduce the uncertainty

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with respect to sampling error caused from relying on field measurements alone (Hoover 2008; Mascaro et al. 2011). A variety of Earth-orbiting sensors, both active and passive, have been used singly, or in combination, for one-time assessment of forest biomass (e.g. Saatchi et al. 2011; Kellndorfer et al. 2013). The resulting gridded biomass data sets have spatial resolutions ranging from 30 m to 1 km and domains ranging from regional, to national, to global. Less commonly, remote sensing has been used to estimate large-area changes in biomass (e.g. Main-Knorn et al. 2013).

New requirements associated with quantifying carbon sequestration in a mitigation context call for more accurate estimates of biomass, and change in biomass, at the landscape scale. The United Nations REDD programme (Reducing Emissions from Deforestation and Forest Degradation) recommended using a combination of remote sensing and ground-based observations for monitoring carbon sequestration (UNFCCC 2009). Airborne Light Detection and Ranging (lidar) have the potential for this application (Wulder et al. 2008; Ferraz et al. 2016), and studies suggest significantly higher accuracy in aboveground biomass estimates developed from lidar compared to those developed from radar or passive optical data (Zolkos, Goetz, and Dubayah 2012).

A high-resolution 3D point cloud provides a clear depiction of the canopy structure, from which biomass can be estimated at the level of plots or individual trees (Duncanson et al. 2014). Individual tree metrics take into account stand density, and therefore may significantly improve AGB (Aboveground Biomass) estimation relative to metrics such as mean canopy height (Duncanson et al. 2015). The success of lidar in tree-level segmentation can depend on tree architecture, and success in detecting biomass change based on repeated lidar surveys will depend on the magnitude of the changes in tree height relative to uncertainty in the biomass estimates. In this study, we evaluated the potential for estimating forest biomass change at the landscape scale in a conifer forest using repeated lidar surveys and tree-level analysis. The change detection results, while not calibrated in this study to a site-specific ground survey, indicate that multiple years of lidar coverage can be an effective tool to evaluate changes in tree growth and mortality as well as landscape-level biomass.

2. Data and methods

2.1. *Overview*

The study aimed to estimate the change in forest biomass based on two lidar data acquisitions (Figure 1). Individual trees were delineated based on point cloud clustering. Tree height and crown area provided the basis for estimation of tree-level biomass using allometry. Change in area-wide biomass was based on the difference in biomass over the interval between lidar acquisitions.

2.2. *Study area*

The area of interest (Figure 2) covers 52.76 km^2 of land located in northwest Oregon (USA). It was delineated based on the availability of commercial lidar data at the beginning and end of a 6-year interval. The area is comprised of actively managed, temperate coniferous forest, and includes 0.44 km^2 of a reservoir. The study area is

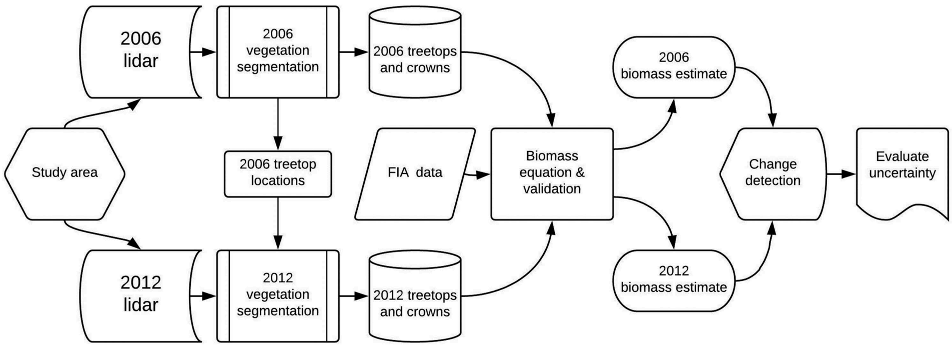

Figure 1. Information flow diagram.

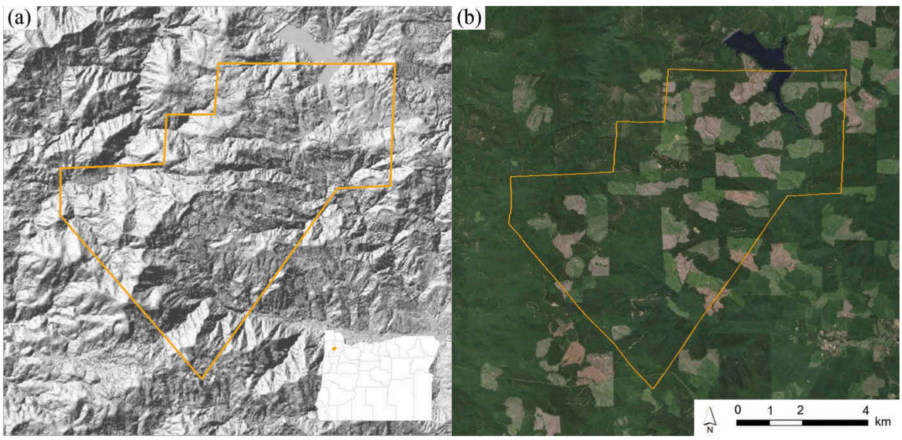

Figure 2. The study area covers 52.76 km^2 of actively managed, temperate coniferous forest in northwest Oregon, USA. Study area polygon over a hill-shaded digital elevation model from the Oregon Department of Geology and Mineral Industries (a). Study area polygon over a Google Earth image from July 2012 (b).

classified as the Coast Range in the Level III Ecoregions of the United States (Omernik 1987). The Oregon Watershed Assessment Manual classifies the region as 'Volcanics,' with steep slopes of basalt composition (OWAM 2001). The area has heavy winter precipitation, mostly in the form of rain rather than snow, from moist air masses moving off the Pacific Ocean to the west. Because of coastal fog influence and fire suppression, wildfire is uncommon, and stand densities are relatively high (greater than 500 trees per hectare) (Tappeiner et al. 1997). Common tree species include conifers, predominantly Douglas fir (*Pseudotsuga menziesii*), but with western hemlock (*Tsuga heterophylla*), Sitka spruce (*Picea sitchensis*), and western red cedar (*Thuja plicata*) also present. Hardwood species, mostly red alder (*Alnus rubra*), occur in riparian areas (Burns and Honkala 1990).

The land in the study area is in private ownership, either by corporations or individuals. Forest potential productivity is relatively high because of the mild climate and deep soils (Hudiburg et al. 2009). Rotation times are on the order of 40–60 years (Campbell, Azuma, and Weyermann 2002).

2.3. *Lidar surveys*

The point cloud data analysed in this study was collected using a small footprint, multiple discrete return lidar sensor. The airborne lidar data was collected in February 2006 and again in October 2012 from a sensor mounted in a Cessna Caravan 208 aircraft operated by Watershed Sciences, Inc. (WSI 2013). The 2006 data was acquired with an Optech ALTM 3100 sensor, and the 2012 data with a Leica ALS60 sensor. Both the sensors scan bi-directionally with oscillating mirrors, producing zig-zag (or sawtooth) scan lines. The effective pulse density was 7.1 pulses/m^2 in 2006 and 9.7 pulses/m^2 in 2012, reflecting improvements in the available technology and protocols over the 6-year period. Specifically, the 2012 acquisition had lower survey altitude and a wider field of view (Table 1). Both lidar point clouds were calibrated in XYZ space using aircraft-based kinematic Global Positioning System (GPS) and static ground GPS collected during the survey. Post-processing routines tied the flight lines together and classified points representing ground and vegetation.

Lidar height accuracy is determined by comparing known ground survey points to the closest laser point (Heidemann 2014). Each lidar data set here was measured against GPS benchmarks and real-time kinematic (RTK) ground control points that were collected during data acquisition. Fundamental Vertical Accuracy (FVA) is an industry standard designed to meet the guidelines presented in the National Standard for Spatial Data Accuracy (NSSDA) (FGDC 1998) and the ASPRS Guidelines for Vertical Accuracy Reporting for LiDAR Data V1.0 (ASPRS 2004). The FVA here was 0.06 m in 2006 and 0.08 m in 2012 (DOGAMI, 2012).

Segmentation was applied to the vegetation-classified points using automated tree segmentation tools based on the work of Li et al. (2012). The algorithm applies horizontal spacing measurements and vertical distribution metrics to delineate and attribute individual trees (QSI 2017). This method is effective at isolating individual trees in complex mixed conifer forests (Zhao, Guo, and Kelly 2012; Li et al. 2012; Jakubowski et al. 2013).

The highest point in each cluster was designated as the treetop and assigned a unique identification number. Minimum bounding polygons were generated for each tree crown using the lidar returns associated with each treetop point (Figure 3). Based

Table 1. Lidar data collection and processing specifications.

	2006 lidar	2012 lidar
Acquisition date	6 February 2006 – 7 February 2006	2 October 2012 – 4 October 2012
Sensor	Optech ALTM 3100	Leica ALS60
Platform	Cessna Caravan 208	Cessna Caravan 208
Data provider	Watershed Sciences, Inc.	Watershed Sciences, Inc.
Coordinate system/units	UTM10, m	UTM10, m
Targeted pulse density	8 ppsm	8 ppsm
Effective pulse density	7.1 ppsm	9.7 ppsm
Survey altitude	1,100 m AGL	900 m AGL
Field of view	28° FOV	30° FOV
Adjacent swath overlap	50% sidelap	60% sidelap
Reported vertical accuracy	0.06 m	0.08 m
File format	LAS 1.2	LAS 1.2

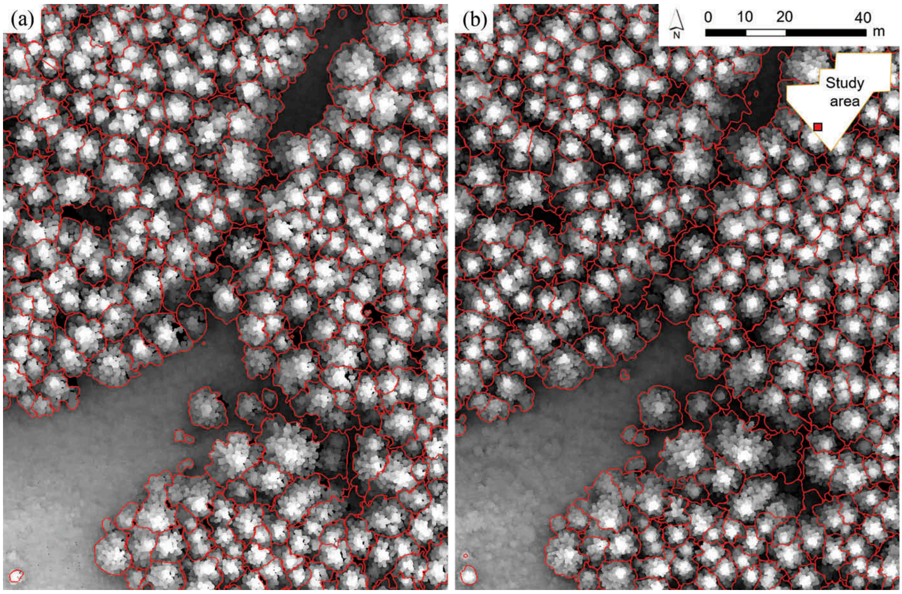

Figure 3. Sample area of individual tree crown segmentation in 2006 (a) and 2012 (b).

on preliminary studies in conifer forests, an initial search radius of 1.68 m was used to calculate the concave hull of each tree, and the raw polygons were buffered by 0.3 m to ensure tree point enclosure. Feature Output attributes included crown area, treetop height, and coordinates. Estimated tree crowns smaller than 1 m^2 were excluded from the analysis, as they most often represent small shrubs or grasses. Minimum tree height for the purposes of this study was 2 m.

To assess change, the 2006 outputs were fed into the segmentation algorithm and used as seeds for the 2012 results. The trees identified in the first lidar data set that were retained in the second set maintained their unique IDs and the treetop locations remained fixed. New crown polygons were generated to reflect recruitment. Removed trees were identified from a threshold of ≥50% reduction in height. New trees appearing in the second set (e.g. regenerating from clear-cuts or from under-segmentation in the 2006 image) were assigned new unique IDs.

Errors in segmenting a lidar point cloud into individual trees take the form of over-segmentation (reporting multiple trees where only one tree exists within the multiple polygons) or under-segmentation (reporting one tree polygon where multiple trees exist within the polygon) (Yin and Wang 2016; Qin et al. 2014; Li et al. 2012). Vegetation segmentation results are sometimes assessed by visual inspection of segmented imagery, as in Figure 3 (Yin and Wang 2016; Qin et al. 2014; Sterénczak and Miścicki 2012). Here, we carried out this type of analysis on the 2012 segmentation over a 0.56 km^2 area of undisturbed land. As a check on under-segmentation in the 2006 image, we counted the number of new trees in the 2012 image greater than 10 m in height, the rationale being that they could not have grown that much in the 6-year interval and hence were present in the 2006 image but undetected.

2.4. Biomass estimation

Tree biomass is commonly estimated by way of allometry, i.e. a regression equation is developed to describe the relationship between field-measured tree properties and corresponding biomass. The equation is then applied to lidar-derived tree metrics (Bortolot and Wynne 2005). It is generally concluded that allometric relationships derived from local or regional data are preferred to more generic relationships developed for national-level assessments (Zhao, Guo, and Kelly 2012). The tree-level reference data used in this study came from the Forest Inventory and Analysis (FIA) national programme of the USDA Forest Service (Woudenberg et al. 2010), specifically the PNW-FIA Integrated Database (Thompson 2015). The input data included 506 plots within the Coast Range ecoregion in Oregon classified as either conifer forest type or non-stocked (<10% stocking in tally trees and seedlings). A total of 14,709 trees (across multiple species) were used to develop the allometric relationships. The predicted variable (aboveground biomass) included all aboveground wood plus foliage.

The crown area for each reference tree was calculated in the Forest Vegetation Simulator (FVS) (Keyser 2017), which estimates crown diameter from diameter at breast height (DBH) along with tree crown ratio (the relative amount of the bole supporting foliage), tree height, stand basal area, latitude and longitude, and/or elevation, depending on the species. The algorithm assumes a circular crown. This FVS-based approach was necessary because crown areas are not routinely measured by FIA field crews. Scatter-plots of tree biomass against tree height and the crown area indicated some curvature to the relationships (Figure 4). A stepwise regression of biomass was developed on simple and quadratic terms (1). Stepwise regression was used to select the most parsimonious model from the potential variables of interest (height and crown area and their quadratic terms); variables needed to be significant at less than $p = 0.15$ to be added to the model and to remain. All terms were significant, with $R^2 = 0.96$ and the Mallow's C_p criterion (Gilmour 1996) indicated using all 4 terms was appropriate. The equation was run without an intercept term (i.e., intercept = 0) in order to constrain the model so that a tree of zero DBH and height would have zero biomass, and to avoid

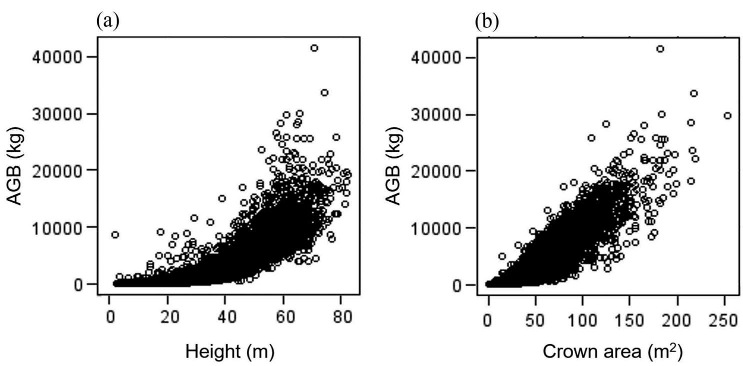

Figure 4. Scatter plots of biomass vs. height (a) and crown area (b) for all trees (N = 14,709) used to develop the AGB prediction model. The source data for this figure is from the FIA and includes trees from both young and mature forests across the Oregon Coast Range ecoregion.

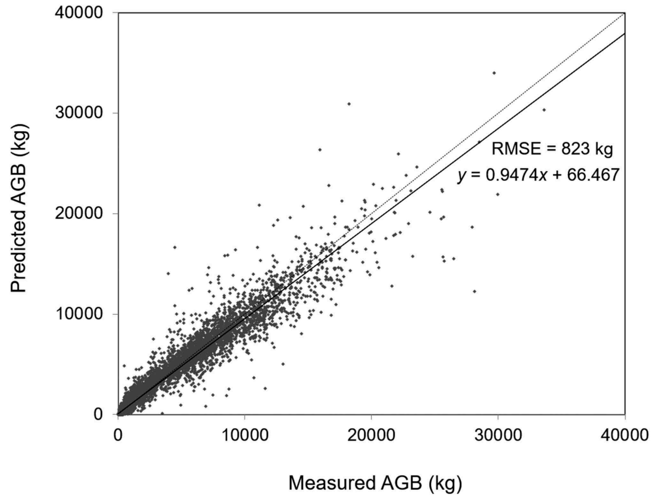

Figure 5. Scatter plot of measured vs. predicted tree biomass for all trees used to develop the AGB prediction model (N = 14,709 trees).

spurious models with no biological meaning. RMSE across all trees was 823 kg, with a small positive bias (Figure 5).

$$AGB = (-55.53 \times H) + (2.386 \times H^2) + (5.062 \times C) + (0.4238 \times C^2) \quad (1)$$

where

AGB = Aboveground Biomass (kg)

H = Tree Height (m)

C = Crown Area (m^2).

Equation (1) was applied to all trees in both lidar data sets to estimate tree-level and aggregate AGB at the beginning and end of the 6-year period. For display purposes, tree centres within each 50 m grid cell were aggregated, and associated tree biomass summed to provide a grid cell average (Figure 6).

3. Results

In the segmentation error assessment for 2012, there were 8,632 trees spread over the test land area, of which 8,372 were true positives (correctly segmented), 230 were negatives (omission) and 30 were false positives (commission). These results signify an over-segmentation rate of 0.3% and an under-segmentation rate of 2.7%. The check on 'new trees' greater than 10 m in height in 2012 found 691, suggesting an under-segmentation rate of 8% for the 2006 survey.

Estimated AGB for the study area averaged 43.6 kg m^{-2} in 2006 and 35.2 kg m^{-2} in 2012, thus 8.43 kg m^{-2} higher in 2006 than in 2012, indicating an average 1.27 kg m^{-2} reduction per year (6.66 years passed between the two surveys). Due to the harvesting activities that occurred between the lidar surveys, some areas showed a relatively large AGB reduction while undisturbed areas showed in a net increase (Figure 7). Estimated total change in biomass over the study interval was −0.45 Tg.

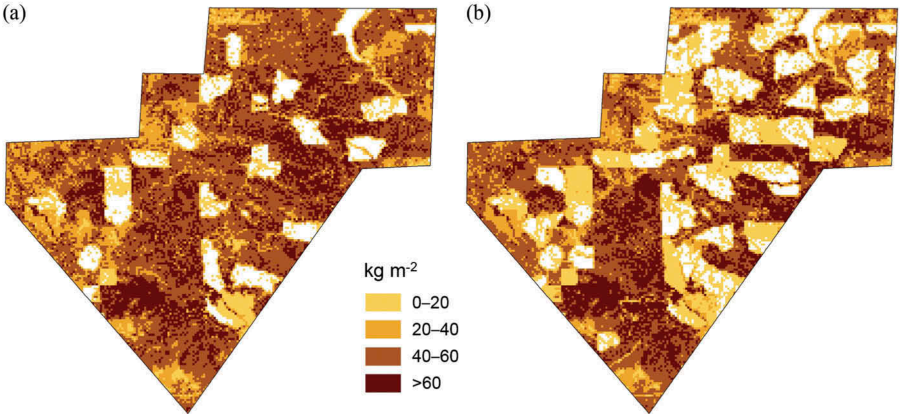

Figure 6. Biomass estimates for 2006 (a) and 2012 (b). White represents areas where no trees were detected.

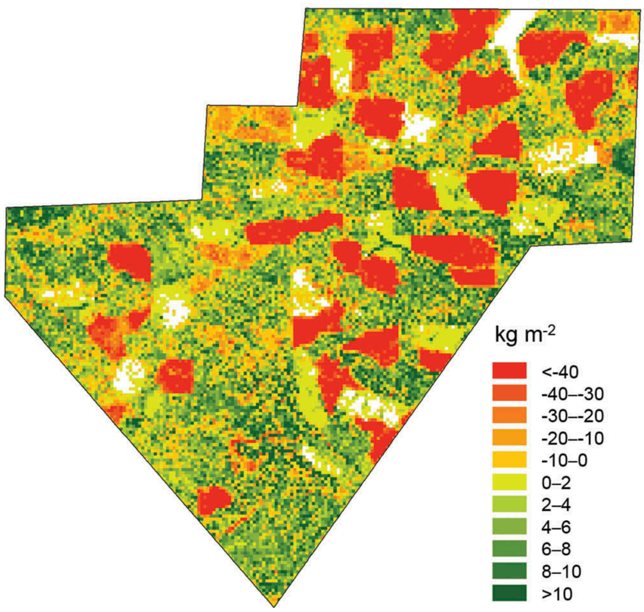

Figure 7. Calculated change in biomass over the 6-year period. White represents areas with no detected change in biomass.

To address the high level of variation across the managed landscape, seven sample areas (250 m x 250 m) were designated by visual inspection to represent each of 3 area types – undisturbed, thinned, and cleared. Undisturbed areas accumulated an average of 1.0 (SD = 0.1) kg m^{-2} $year^{-1}$ compared to losses of −3.5 (SD = 2.6) kg m^{-2} $year^{-1}$ in the thinned areas and −8.0 (SD = 1.5) kg m^{-2} $year^{-1}$ in the cleared areas. Average standing biomass (2012) in the undisturbed, thinned, and cleared sample areas was 54.4 kg m^{-2}, 26.2 kg m^{-2} and 0.4 kg m^{-2} respectively.

Seventy-five percent of the trees existing in 2006 were still standing in 2012 and retained the same unique ID. These surviving trees formed the basis for observing growth rates during various stages in the tree lifecycle. When binned by height, trees of intermediate height (35–40 m) showed the largest biomass increase, with an average 381 kg gain per tree over the 6-year period (Figure 8). The average height growth per tree between the two surveys was 3.6 m (Figure 9), which is large relative to the uncertainty in estimated tree height (Vauhkonen et al. 2011; Kaartinen et al. 2012).

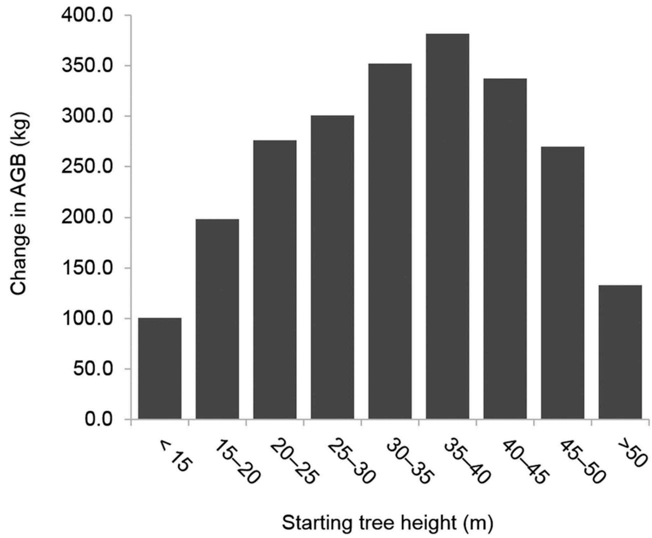

Figure 8. Change in aboveground biomass between 2006 and 2012 for trees that were not harvested (N = 499,411 trees).

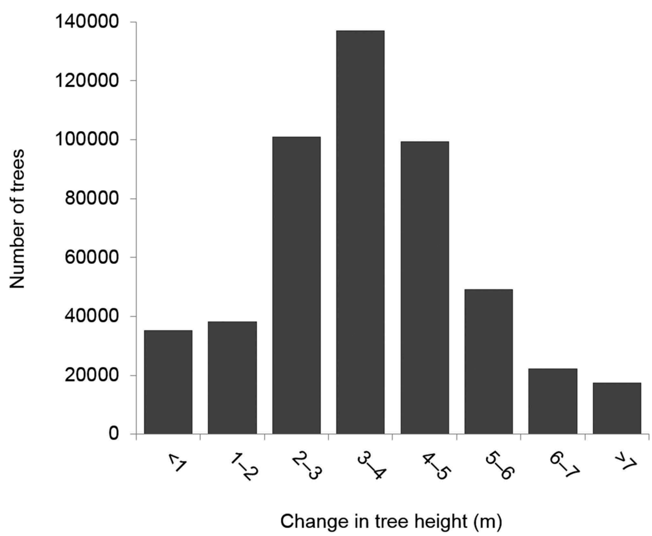

Figure 9. Change in tree height between 2006 and 2012 for the trees that were not harvested (N = 499,411 trees).

Of the 25% of trees in 2006 that did not survive, the majority were in areas that were apparently cleared or thinned. Using a threshold biomass loss rate of 4.5 kg m^{-2} $year^{-1}$ (i.e. a harvest of ≥30 kg m^{-2}), approximately 3% of the study area was harvested per year. Tree mortality in the undisturbed sample areas (as a proportion of total trees) was 0.5% or about 0.1% per year. Recruitment of new trees into the class of relatively short trees was also about 0.1% per year.

4. Discussion

4.1. *Uncertainties in the approach*

Vegetation segmentation algorithms rely on a relatively high-resolution lidar point cloud (Li et al. 2012; Duncanson et al. 2014). The general recommendation for differentiating individual trees is a targeted density of ≥8 pulses/m^2 (Heidemann 2014), as was achieved in our 2012 survey. Our under-segmentation rate of approximately 3% in 2012 compares to 6% in a similar study in a mixed conifer forest (Li et al. 2012). The higher under-segmentation that we observed in the 2006 survey (8%) is likely related to the lower effective pulse density. As was the case in Li et al. (2012), we found more under-segmentation than over-segmentation. Note that understorey trees may be undetected either in the lidar point cloud or the visual inspection, thus adding uncertainty to the biomass estimates and the accuracy assessment. Much higher pulse densities than were used in our study are technically possible, and would more effectively capture understorey trees (Hamraz, Contreras, and Zhang 2017). Our study area is actively managed forestland and contains mostly even-age stands, hence with relatively low canopy complexity (Tappeiner et al. 1997). Segmentation errors in conifer forests may be lower than those in broadleaf forests because the conical shape of the individual tree canopies makes the tops easier to locate.

The significant under-segmentation in our 2006 dataset would cause an underestimate of total biomass. Its impact on the estimated change in biomass relative to 2012 would depend on the rate of harvests or other disturbances (in which case biomass loss would be underestimated) vs. land undisturbed (in which case biomass gain would be overestimated). These results emphasize the importance of continuity in methodology between repeated lidar surveys, and the need to characterize uncertainty in tree segmentation.

Our estimates of tree-level biomass from lidar-derived height and crown area rely on a statistical model (1). Inherent within the model is the uncertainty of measured biomass for the reference trees used to develop it. Biomass for the trees in the PNW-FIA database used here was estimated from tree height (measured by laser rangefinder), DBH, and crown areas (Woudenberg et al. 2010). An independent check indicated an RMSE of approximately 12% of mean biomass for Douglas-fir bolewood using the PNW-FIA allometry (Poudel and Temesgen 2016). However, assuming no error in the reference tree biomass, our model using tree height and crown area to predict AGB (1) had a high R^2 and low bias (Figure 5).

It was beyond the scope of this study to make tree level measurements of height and crown area at the time of the lidar flights. Thus, we have assumed an equivalence of height and crown area as we inferred from our lidar data and as derived from FIA observations in the region – an additional source of uncertainty. Vauhkonen et al. (2011) and Kaartinen et al. (2012) reviewed the results of multiple tree-level studies and reported the accuracy of lidar tree height generally better than 0.5 m. Jakubowski et al. (2013) in a study with many similarities to ours in terms of lidar data, segmentation algorithm, type of forest, and range of tree heights, reported an R^2 of 0.93 for observed and lidar-based tree height. Validation of crown area estimates is more difficult and less often reported in the literature (Yin and Wang 2016). However, Jakubowski et al. (2013) reported that a concave hull approach for delineating planar crown area tends to produce more complex crown area shapes than in the case with other approaches, hence better capturing actual crown shapes.

For operational use in carbon sequestration programmes such as REDD+, an individual tree-based monitoring approach would require ground surveyed tree measurements for validation of height estimates. Plot-level biomass studies would likewise be needed to validate lidar-based biomass estimates.

Alternative approaches to using point cloud lidar for biomass estimation rely on mean top of canopy height or Lorey's height (tree size weighted mean height) (Wulder et al. 2012; Asner and Mascaro 2014; Sheridan et al. 2015). However, by accounting for variable crown sizes and tree top heights, tree segmentation generally brings more information to bear on estimating biomass compared to models based on canopy height alone (Bright, Hicke, and Hudak 2012; Gleason and Im 2012; Duncanson et al. 2015). Isolation of individual trees likely results in more precise biomass estimates in part because the inclusion of crown area helps account for the influence of competition on the height-to-biomass relationship.

4.2. *Estimation of biomass, biomass change, growth, and mortality*

4.2.1. *Biomass*

Past AGB studies over larger domains offer a point of comparison for the current study. Satellite data in combination with forest inventory data has been used in these studies to achieve widespread coverage. Source platforms include the Shuttle Radar Topography Mission (SRTM) (Kellndorfer et al. 2013), the Moderate-resolution Imaging Spectrometer (MODIS) (Blackard et al. 2008; Wilson, Woodall, and Griffith 2013), and Landsat (Turner et al. 2016). The resulting gridded biomass data sets have a spatial resolution ranging from 30 m to 250 m and reference years varying between 2000 and 2012 (Table 2). Comparisons over our study area are presented here in terms of kgC m^{-2} of Aboveground Live Carbon (ALC), the native units in some of these studies. AGB was

Table 2. Results from previous studies were clipped to the current study area to extract estimates for a direct comparison.

Study	Reference year	Source data	ALC (kg m^{-2})
Current study	2006	Lidar	21.8
Current study	2012	Lidar	17.6
Turner et al. (2016)	2011	Landsat time series/carbon cycle model	16.2
Kennedy (2016)	2012	Landsat	11.0
Wilson, Woodall, and Griffith (2013)	2009	MODIS	13.3
Kellndorfer et al. (2013)	2000	STRM/Landsat	15.6
Blackard et al. (2008)	2001	MODIS	12.6

multiplied by 0.5 for conversion to ALC, a standard equation in the forest industry (Zald et al. 2016; Wilson, Woodall, and Griffith 2013; Blackard et al. 2008; Hoover 2008).

The current study estimate of 17.6 kgC m^{-2} for ALC in 2012 compares most closely with an estimate of 16.2 kgC m^{-2} for 2011 in the study of Turner et al. (2016). There, biomass was simulated over the interval 1985–2011 based on a time series of Landsat data, to characterize the disturbance regime, and a carbon cycle process model in which growth rates were calibrated with forest inventory plot data at the ecoregion scale. A MODIS-based estimate for 2009 was 13.3 kgC m^{-2} (Wilson, Woodall, and Griffith 2013), but a high level of local accuracy would not be expected from this relatively coarse resolution sensor, and several continental biomass maps have shown a residual negative bias of 1.7–2.7 kgC m^{-2} when compared to high-resolution lidar-derived biomass maps at a local scale (Huang et al. 2015). The characteristic scale of disturbances, mostly clear-cut harvest, in managed forest landscapes in western Oregon is on the order of 250 m (Turner, Cohen, and Kennedy 2000). A MODIS-based estimate for 2001 was 12.6 kgC m^{-2}, which compares to an SRTM (around 90 m resolution) of 15.6 kgC m^{-2} for 2000 (Kellndorfer et al. 2013). These studies all relied on FIA inventory data for reference using diverse approaches, but effects of different types of sensors (active vs. passive) and different spatial resolutions introduce wide variation in tree carbon stock estimates.

In an actively managed forest over a large enough area, average biomass is expected to remain steady over time (Harmon and Marks 2002). This assumption relies on the objective of a sustained yield for harvestable wood. This study found a small decrease on average in tree biomass over the study interval, with a high degree of heterogeneity in biomass gain or loss (Figure 7). The observed harvest rate of approximately 3% of total area per year is indicative of a rotation age of 33 years, somewhat lower than expected even in the highly productive Coast Range ecoregion in Oregon (Campbell, Azuma, and Weyermann 2002; Hudiburg et al. 2009). Global Forest Watch, using Landsat data, indicates more forest cover lost than gained in our study area between 2001 and 2014 (GFW (Global Forest Watch) 2017), consistent with a high rate of disturbance. However, several industrial forest owners in Western Oregon manage areas much greater than our 53 km^2 study area, thus no overall conclusions can be made about whether forestland owners in the region are harvesting at a sustainable rate. Turner et al. (2016) reported a harvest rate of 1.1% per year over the 1985–2011 period for the Coast Range ecoregion in Oregon and Washington, but that included some areas such as Olympic National Park, where harvest does not occur.

4.2.2. *Tree growth*

The biomass growth rate of 1.0 kg m^{-2} year^{-1} for undisturbed areas is similar to the rates of wood production in Coast Range ecoregion biomass productivity studies (e.g. Gholz 1982) and compilations of USFS FIA plot data (Van Tuyl et al. 2005; Hudiburg et al. 2009). A lidar-based study in conifer forests of the Northern Rocky Mountains detected an average AGB increase over 6 years of 0.8 kg m^{-2} year^{-1} in non-harvested areas (Spangler and Vierling 2011). Tree height growth is typically asymptotic with DBH and age, whereas biomass growth may continue (Sillett et al. 2010). However, for Coast Range Douglas-fir, specifically, DBH is still increasing with height out to over 50 m of height (Hanus, Marshall, and Hann 1999), the high end of the height range in this study. Uncertainty in estimated biomass growth would nevertheless increase as trees approached maximum height because rates of height growth decrease (Ryan, Phillips, and Bond 2006; Means and Sabin 1989).

4.2.3. *Mortality*

Rates of tree mortality in unharvested areas were relatively low here, i.e. 0.02 kg m^{-2} $year^{-1}$ (0.04% of biomass m^{-2} $year^{-1}$, 0.1% of trees). Hudiburg et al. (2009) reported AGB mortality, here approximated from total tree biomass mortality, on the order of 0.06 kg m^{-2} $year^{-1}$ in Coast Range forests of Oregon and Washington. However, the FIA plots on which that estimate was based likely included a wider range of stand age and management approaches. Acker et al. (2002) found bolewood mortality of 0.01 to 0.03 kg m^{-2} $year^{-1}$ for young conifer stands in the Cascade Mountains of Oregon. Repeated tree-level lidar surveys offer an opportunity to evaluate mortality more comprehensively than plot-level studies, hence may improve capacity to evaluate possible increases in mortality in response to climate change (van Mantgem et al. 2009).

4.3. *Potential applications*

Accurate measurement of forest biomass and growth is a critical component in quantifying carbon stocks and sequestration rates (Temesgen et al. 2015). Although the United Nations REDD+ programme is still operating on the basis of voluntary funding, it has the potential to become quite expansive. Studies of methods for monitoring and reporting carbon credits in the context of REDD+ generally support remote sensing – and specifically lidar-based – approaches, combined with field measurements (GOFC-GOLD 2016). Our study indicates the feasibility of tracking landscape-scale biomass change based on analysis of individual trees. However, changing instrumentation and industry standards over the interval of interest in biomass change studies can be problematic, which points to possible advantages of space-borne lidar missions, e.g. the Global Ecosystem Dynamics Investigation Lidar (GEDI 2018).

Tree-level estimates of biomass are also relevant to modelling wildfire spread and wildfire carbon emissions because the characterization of fuel loads typically includes multiple classes of fuel types, some of which are related to tree size, tree density, or tree height (Ziegler et al. 2017). Knowledge about forest structure, notably live tree density and size, and changes in forest structure is indeed relevant to multiple ecological questions relating to biodiversity and ecosystem function (Reilly and Spies 2015).

Fusion of lidar-derived tree data with multispectral and hyperspectral data has the potential to provide further information relevant to forested lands management (Asner et al. 2012). Tree health can be assessed with four-band, visible and NIR, multispectral imagery (Lawley et al. 2016). Unique spectral signatures for specific tree species can be extracted from hyperspectral imagery, especially in the NIR and shortwave infrared portions of the spectrum (Baldeck et al. 2015), with accuracies reported at 60–90% (Jones, Coops, and Sharma 2010; Alonzo, Bookhagen, and Roberts 2014). Species classification of individual trees in forested areas could be linked to species-specific allometry and hence reduce uncertainty in biomass mapping.

5. Conclusions

Forests represent significant sources and sinks of carbon, and accurate monitoring of forest carbon stocks at landscape to regional scales is relevant to understanding the global carbon cycle and mitigating the rise in atmospheric CO_2. Airborne lidar permits tree-level analysis of tree carbon stocks based on indicators such as tree height and crown attributes. Here we established the potential for tracking tree-level growth and mortality using repeated lidar surveys, and aggregating results to estimate landscape scale biomass change. In our managed conifer forest landscape in the temperate zone, an interval of 6 years was sufficient to detect relevant changes in tree height and biomass. The tree-level approach to characterizing forest structure and dynamics has a wide array of potential applications.

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