



Quantifying aboveground forest carbon pools and fluxes from repeat LiDAR surveys

Andrew T. Hudak ^{a,*}, Eva K. Strand ^{b,1}, Lee A. Vierling ^b, John C. Byrne ^a, Jan U.H. Eitel ^{b,c}, Sebastián Martinuzzi ^d, Michael J. Falkowski ^e

^a Rocky Mountain Research Station, United States Forest Service, Moscow, ID, United States

^b Forest, Rangeland, and Fire Sciences, University of Idaho, Moscow, ID, United States

^c McCall Outdoor Science School, University of Idaho, McCall, ID, United States

^d Forest and Wildlife Ecology, University of Wisconsin, Madison, WI, United States

^e School of Forest Resources and Environmental Science, Michigan Technological University, United States

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ABSTRACT

Sound forest policy and management decisions to mitigate rising atmospheric CO₂ depend upon accurate methodologies to quantify forest carbon pools and fluxes over large tracts of land. LiDAR remote sensing is a rapidly evolving technology for quantifying aboveground biomass and thereby carbon pools; however, little work has evaluated the efficacy of repeat LiDAR measures for spatially monitoring aboveground carbon pools through time. Our study objective was therefore to evaluate the use of discrete return airborne LiDAR for quantifying biomass change and carbon flux from repeat field and LiDAR surveys. We collected LiDAR data in 2003 and 2009 across ~20,000 ha of an actively managed, mixed conifer forest landscape in northern Idaho. The Random Forest machine learning algorithm was used to impute aboveground biomass pools of trees, saplings, shrubs, herbaceous plants, coarse and fine woody debris, litter, and duff using field-based forest inventory data and metrics derived from the LiDAR collections. Separate predictive tree aboveground biomass models were developed from the 2003 and 2009 field and LiDAR data, and biomass change was estimated at the plot, pixel, and landscape levels by subtracting 2003 predictions from 2009 predictions. Traditional stand exam data were used to independently validate 2003 and 2009 tree aboveground biomass predictions and tree aboveground biomass change estimates at the stand level. Over this 6-year period, we found a mean increase in tree aboveground biomass due to forest growth across the non-harvested portions of 4.1 Mg/ha/yr. We found that 26.3% of the landscape had been harvested during this time period which outweighed growth at the landscape level, resulting in a net tree aboveground biomass change of −5.7 Mg/ha/yr, and −2.3 Mg/ha/yr in total aboveground carbon, summed across all the aboveground biomass pools. Change in aboveground biomass was related to forest successional status; younger stands gained two- to three-fold less biomass than did more mature stands. This result suggests that even the most mature forest stands are valuable carbon sinks, and implies that forest management decisions that include longer harvest rotation cycles are likely to favor higher levels of aboveground carbon storage in this system. A 30-fold difference in LiDAR sampling density between the 2003 and 2009 collections did not affect plot-scale biomass estimation. These results suggest that repeat LiDAR surveys are useful for accurately quantifying high resolution, spatially explicit biomass and carbon dynamics in conifer forests.

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1. Introduction

Forests cover approximately one third of the Earth's land surface and have a tremendous capacity to store and cycle carbon (e.g. Dixon et al., 1994; Harmon & Marks, 2002). Indeed, the total carbon stored in forested ecosystems, including live and dead wood, litter, detritus, and soil, exceeds the amount of carbon found in the atmosphere (FRA, 2005; Heath et al., 2010). Accelerated pressure on forest resources to provide a wide range of environmental services,

including mitigation of atmospheric carbon dioxide, has given rise to concerted study of how change in forest cover and land use affects emissions of CO₂ to the atmosphere (McKinley et al., 2011), and how forests may be managed for carbon benefits (Hines et al., 2010). Because forest change is a highly dynamic, broad scale phenomenon, such efforts to understand the carbon balance of forests via frameworks such as the Reduction of Emissions from Deforestation and forest Degradation (REDD; e.g. Gibbs et al., 2007) in developing nations and through various other carbon Measuring, Reporting, and Verification (MRV) protocols require repeatable, objective, and accurate remote sensing methods for estimating aboveground forest carbon pools and fluxes over large areas (Goetz & Dubayah, 2011). Improved quantitative methods at the landscape level, where forest

* Corresponding author. Tel.: +1 208 883 2327; fax: +1 208 883 2318.

E-mail address: ahudak@fs.fed.us (A.T. Hudak).

¹ Equally contributing authors.

management decisions are made, could lead to more accurate forest carbon accounting at the national level, where policy decisions are made (Heath et al., 2010; Hines et al., 2010).

Remote sensing approaches for quantifying components of forest biomass are rapidly evolving. Vine and Sathaye (1997) suggested that to quantify aboveground forest carbon pools and fluxes across broad extents, it is important to combine remote sensing techniques with carbon estimation methods that are based on existing standard forest inventory principles. Light Detection And Ranging (LiDAR) has been employed to successfully quantify vertical structure and forest attributes such as canopy height distribution, tree height, and crown diameter (e.g. Hudak et al., 2002; Lefsky et al., 2002; Nilsson, 1996; Yu et al., 2008). Robust methods for producing wall-to-wall maps of aboveground forest carbon pools using single-date LiDAR combined with field data collections and Monte Carlo statistical methods have recently been developed with errors <1% (Gonzalez et al., 2010). Single-date LiDAR combined with field data and satellite imagery was used to quantify carbon pools at high spatial resolution at the landscape level (~10⁶ ha) in Hawaii (Asner et al., 2011), and recently, spaceborne LiDAR was used in combination with spaceborne radar and MODIS data to quantify tropical carbon stocks across three continents (Saatchi et al., 2011).

Observing landscape level changes in carbon pools (i.e. carbon fluxes) at high spatial resolution requires repeat acquisition of LiDAR data via aircraft or satellite sensors. However, few studies have used repeat LiDAR acquisitions for any purpose. Dubayah et al. (2010) used repeat collections of waveform LiDAR data from the NASA Laser Vegetation Imaging Sensor (LVIS) instrument in 1998 and 2005 to determine change in forest height in a humid tropical forest of Costa Rica, and were able to infer whether primary and secondary tropical forests were sources, sinks, or neutral with respect to their carbon emissions during the intervening time interval. Bater et al. (2011) assessed the reproducibility of height and intensity metrics derived from multiple LiDAR acquisitions of coniferous forest on Vancouver Island collected on the same day and found that most metrics provided stable repeated measures of forest structure. Yu et al. (2004) applied an automated, object-oriented tree-matching algorithm to two LiDAR acquisitions collected two years apart to estimate height growth of ~5 cm at the stand level and 10–15 cm at the plot level. These studies show promise for multi-temporal LiDAR based assessment of forest dynamics and carbon flux. However, as LiDAR technology continues to evolve, much additional work is needed to extend this approach and narrow uncertainties in the quantification of forest carbon dynamics. Of particular importance are areas of active forest management (e.g., timber harvest) comprised of different forest successional and structural stages (Falkowski et al., 2009). Understanding biomass and carbon dynamics across varied forest management and successional regimes is highly useful for predictive modeling and carbon management because it connects forest ecosystem processes such as growth and harvest with landscape-level carbon pools and fluxes.

The primary objective of this research is to utilize repeat LiDAR and field plot surveys and statistical modeling to predict biomass pools and estimate rates of aboveground carbon flux in managed mixed conifer forests of the Northern Rocky Mountains, USA. Specifically, we utilize field forest inventory data and airborne LiDAR data collected during the summers of 2003 (Hudak et al., 2006) and 2009 to quantify the effects of forest growth and timber harvest on carbon pools of trees, saplings, shrubs, coarse and fine woody debris, herbaceous plants, litter, and duff across an actively managed forest landscape, and examine relationships among changes in these pools during this 6-year interval with respect to forest height and successional status. The study serves a broader objective of demonstrating a repeatable methodology for inventory and monitoring of forest carbon pools and fluxes across actively managed forest landscapes to support much needed carbon measuring, reporting, and verification methodologies over time.

2. Methods

2.1. Study area

The study is centered on Moscow Mountain (~20,000 ha; Latitude 46° 48' N, Longitude 116° 52' W), located in the Palouse Range in Northern Idaho, USA (Fig. 1). The area is topographically complex, ranging from 770 m to 1516 m in elevation. Climate is characterized by a warm dry summer and fall, and a wet winter and spring when most of the mean annual average precipitation of 630–1015 mm falls in the form of snow in the winter and rain in the spring. Vegetation is primarily comprised of temperate mixed-conifer forest with dominant species being ponderosa pine (*Pinus ponderosa* C. Lawson var. *scopulorum* Engelm.), Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco var. *glauca* (Beissn.) Franco), grand fir (*Abies grandis* (Douglas ex D. Don) Lindl.), western red cedar (*Thuja plicata* Donn ex D. Don), and western larch (*Larix occidentalis* Nutt). Habitat types include: ponderosa pine series at xeric sites on southern and western aspects; Douglas-fir and grand fir series on moister sites, and cedar/hemlock series at mesic sites on northern and eastern aspects (Cooper et al., 1991). Volcanic ashcap is an important component of the soil structure across the study area, especially on northeastern aspects, and increases soil water holding capacity (Kimsey et al., 2011). The land ownership is dominated by private timber companies with many interspersed private and public land inholdings. The variety of habitat types and management strategies of the landowners has created a forest that is diverse in species composition, stand age, and structure, representing a variety of biophysical settings and forest successional stages (Falkowski et al., 2009; Martinuzzi et al., 2009). Major disturbances occurring during the time period 2003 to 2009 included harvest, thinning, and prescribed fires associated with forest management. The study area is bounded by croplands associated with dryland agriculture to the north, west, and south.

An overview of the methodology is diagrammed in Fig. 2.

2.2. LiDAR surveys and data processing

LiDAR data were collected during the summers of 2003 (by Horizons, Inc., Rapid City, SD, USA), 2007 (by Surdex, Inc., Chesterfield, MO, USA) and 2009 (by Watershed Sciences, Inc., Portland, OR, USA). The extent of the 2003 LiDAR survey was 32,708 ha and included much agricultural land surrounding the contiguous forest block, while that of the 2009 survey was 19,889 ha of the core contiguous forest (Fig. 1). As a cost-saving measure to maximize repeat coverage of the forested area of interest, the 2009 survey was purposely contracted to be outside of a relatively small area (840 ha) of forested land flown just two years prior in 2007 (Fig. 1). Fig. 3 illustrates at a single field plot the dramatic difference in LiDAR survey point densities between 2003 (0.4 points/m²) and 2009 (nearly 12 points/m²); the point density of the 2007 LiDAR survey was intermediate at almost 6 points/m². All three LiDAR systems operated at 1064 nm. Other characteristics of the three LiDAR surveys are provided in Table 1.

The LiDAR data delivered as binary files were converted to ASCII text files for processing, with ~0.5 million points per tile. The relevant attributes of each LiDAR point included: x and y coordinates, absolute elevation (z), the number of LiDAR returns and the return number in the pulse, as well as the unnormalized return intensity ranging from 0 to 255.

Points were converted from text format into the ArcInfo coverage format using the GENERATE command in Arc Macro Language (AML). The ground returns were separated from the vegetation returns using multiscale curvature classification (MCC, Evans & Hudak, 2007). The scale parameter used in the MCC AML was set to match the LiDAR post-spacing. We created a digital terrain model (DTM) of 1 m resolution from the classified ground returns through iterative finite

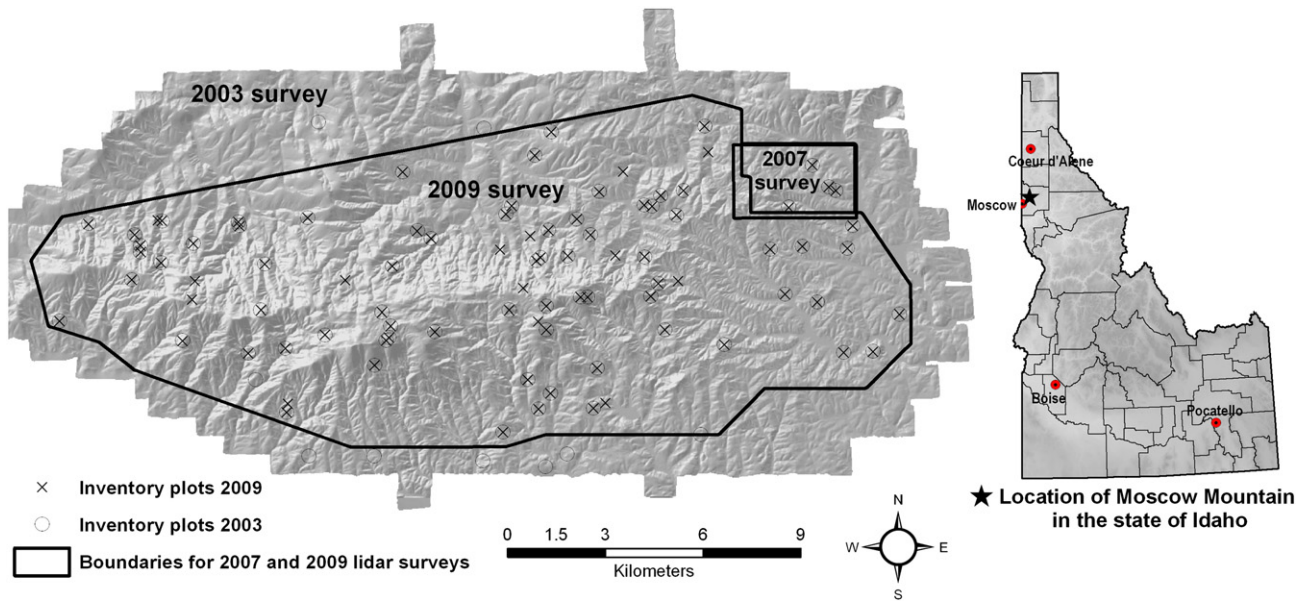


Fig. 1. Location of the Moscow Mountain study area in north central Idaho. The extent of the digital terrain model (DTM) reflects the boundary of the 2003 LiDAR survey.

distance (IFD) interpolation of the z values called by the TOPOGRID function in ArcInfo (ESRI, Redlands, CA, USA). Because of the high data volumes, it was necessary to process the LiDAR data in 10 independent yet overlapping blocks that were later merged together. Care was taken not to introduce edge effects in each block by removing the overlapping edge pixels prior to merging. Vegetation height for each LiDAR return was computed by subtracting the value of the DTM from the LiDAR z -value.

LiDAR vegetation canopy height, density, and intensity metrics (Table 2) were computed from all LiDAR datasets based on the height, density, and intensity of the LiDAR returns within $20\text{ m} \times 20\text{ m}$ grid cells across the study area with a script coded in the R language (R Development Core Team, 2007). The 1 m DTMs were resampled to 20 m by the bilinear resampling method in ArcInfo Grid to match the origin, extent, and grain of the LiDAR canopy metrics. Topographic metrics (Table 2) were derived from the 20 m DTMs.

The 2007 and 2009 metric layers overlapped in a 146 ha area having terrain and forest structure representative of the rest of the 2007 survey. No harvest activity occurred in this overlap area between the 2007 and 2009 surveys. Height measures were calibrated by the

LiDAR vendors but intensity measures were not. The 2007 intensities had a mean of 108.6 while the 2009 intensities had a mean of 93.6 within the 146 ha area of overlap. Therefore, a simple linear transformation function was developed to reduce the 2007 intensity values to better match the 2009 intensity values. From the population of 3901 pixels, 91% of the 2009 minimum intensities were equal to 0 while only 85% of the 2007 minimum intensities were equal to 0. Meanwhile, only 0.05% of the 2009 maximum intensities were equal to 255 while 0.8% of the 2007 maximum intensities were equal to 255 (i.e., saturated). To preserve the zeroes while applying proportionately larger correction to the higher 2007 intensities, we forced the linear model intercept to zero, leaving the equation $y = mx$, where $y = 2009$ intensity, $x = 2007$ intensity, and $m = \text{slope}$. The 0th, 5th, 10th, 25th, 50th, 75th, 90th, 95th, and 100th percentiles from the 2007 and 2009 intensity distributions were bound together to form x and y . This simple linear regression model solved to $y = 0.8320638x$ ($\text{RMSE} = 26.15$, $\text{Adj. } r^2 = 0.95$, $p < 0.0001$). The intensity values of all the 2007 returns were then multiplied by the slope coefficient (0.8320638), and $20\text{ m} \times 20\text{ m}$ grids of the adjusted 2007 intensity metrics were subsequently regenerated using the R script and then

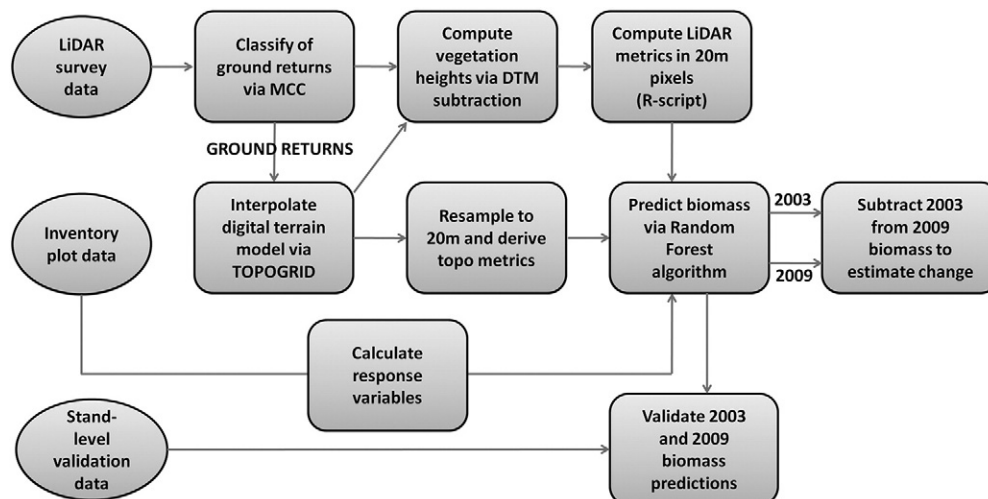


Fig. 2. Procedure for predicting biomass from LiDAR and inventory plot data in 2003 and 2009. Independent predictions of aboveground biomass were subtracted to estimate biomass change.

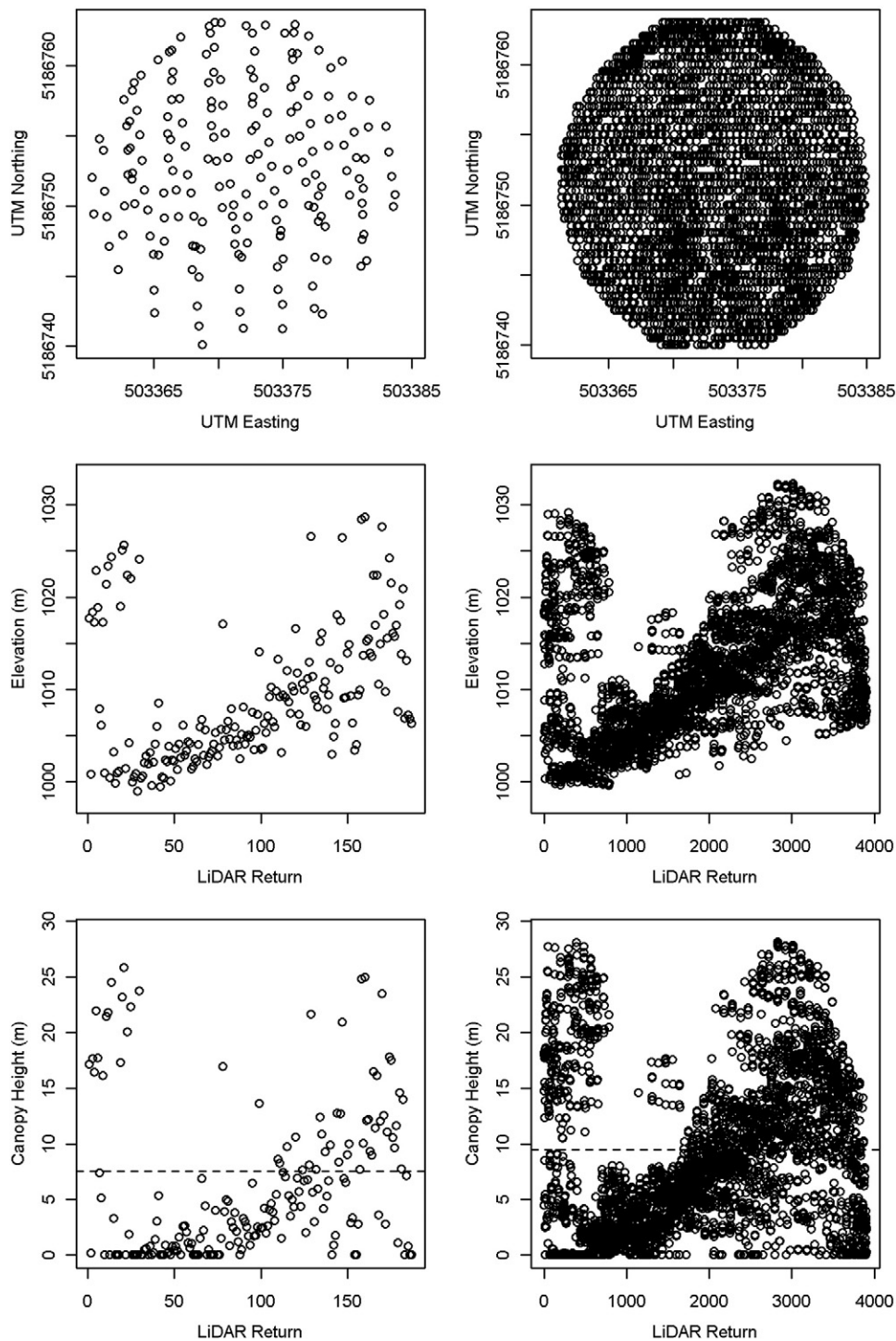


Fig. 3. Comparison of LiDAR survey point densities in 2003 (left) and 2009 (right) at the scale of a single undisturbed 0.25-ha inventory plot (#2802), as viewed from overhead (top) and from the side before (middle) and after (bottom) detrending for topography. Note that despite the dramatic difference in point density between the two surveys, the vertical pattern of points indicative of canopy structure is consistent. Mean height of non-ground returns (>0 m) in this plot (as indicated by the dotted horizontal lines) increased from 7.5 m in 2003 to 9.5 m in 2009.

merged with the 2009 intensity metrics to produce visually seamless mosaics of the intensity metrics across the combined extent of the 2007 and 2009 LiDAR surveys. When merging the 2007 and 2009 metrics, priority was given to the 2009 metrics in the 146 ha overlap area.

Rasters of all metrics were generated with exactly the same origin and extent defined so that the pixels exactly overlaid. These $20\text{ m} \times 20\text{ m}$ (400 m^2) pixels constituted the target observations for

imputing predictive biomass maps based on the 400 m^2 reference plots.

2.3. Field surveys and data processing

Because the extent of the LiDAR surveys changed from 2003 to 2009, the survey areas were independently stratified by elevation, isolation (2003) or slope and aspect (2009), and canopy cover in

Table 1

Acquisition parameters of the 2003, 2007, and 2009 LiDAR surveys.

Survey date	Altitude above ground	LiDAR system	Multiple returns	Footprint diameter	Scan angle	Average post spacing	Average point density
Summer 2003	2438 m	ALS 40	Up to 3/pulse	30 cm	+/- 18°	1.58 m	0.40/m ²
7 July 2007	1219 m	ALS 50	Up to 4/pulse	30 cm	+/- 15°	0.41 m	5.98/m ²
30 June 2009	2000 m	ALS 50	Up to 4/pulse	30–45 cm	+/- 14°	0.29 m	11.95/m ²

stratified random sampling designs. Elevation was obtained from a USGS DTM, and an insolation layer calculated using Solar Analyst (Fu & Rich, 1999). Because the spatial variance in the insolation

Table 2

LiDAR-derived canopy height, intensity, density, and topographic metrics considered as candidate variables for predictive biomass models.

Variable and description
HMEAN Height mean
HMAX Height maximum
HMDAD Height median absolute deviation
HSD Height standard deviation
HVAR Height variance
HSKEW Height skewness
HKURT Height kurtosis
HCV Height coefficient of variation
H05TH Height 5th percentile
H10TH Height 10th percentile
H25TH Height 25th percentile
H50TH Height 50th percentile (median)
H75TH Height 75th percentile
H90TH Height 90th percentile
H95TH Height 95th percentile
HIQR Height interquartile range
HMODE Height mode
HNMODES Number of height modes
HMRANGE Height mode range
IMIN Intensity minimum
IMAX Intensity maximum
IMEAN Intensity mean
IMAD Intensity median absolute deviation
ISD Intensity standard deviation
IVAR Intensity variance
ISKEW Intensity skewness
IKURT Intensity kurtosis
ICV Intensity coefficient of variation
I05TH Intensity 5th percentile
I10TH Intensity 10th percentile
I25TH Intensity 25th percentile
I50TH Intensity 50th percentile (median)
I75TH Intensity 75th percentile
I90TH Intensity 90th percentile
I95TH Intensity 95th percentile
IIQR Intensity interquartile range
DENSITY Canopy density (Vegetation returns/Total returns × 100)
STRATUM0 Percentage of ground returns ≤ 0.15 m in height
STRATUM1 Percentage of non-ground returns > 0.15 m and ≤ 1.37 m in height
STRATUM2 Percentage of vegetation returns > 1.37 m and ≤ 5 m in height
STRATUM3 Percentage of vegetation returns > 5 m and ≤ 10 m in height
STRATUM4 Percentage of vegetation returns > 10 m and ≤ 20 m in height
STRATUM5 Percentage of vegetation returns > 20 m and ≤ 30 m in height
STRATUM6 Percentage of vegetation returns > 30 m in height
TEX Standard deviation of non-ground returns > 0.15 m and ≤ 1.37 m
CRR Canopy relief ratio (Pike & Wilson, 1971)
DTM Elevation (meters)
CTI Compound topographic index (Moore et al., 1993)
DIS Dissection coefficient (Evans, 1972)
ERR Elevation relief ratio (Pike & Wilson, 1971)
HLI Hierarchical landscape index (McCune & Keon, 2002)
HSP Hierarchical slope position (Murphy et al., 2010)
LND Landform (McNab, 1989)
SPS Slope position
TRA Transformed solar-radiation aspect index (Roberts & Cooper, 1989)
TRI Topographic ruggedness index (Riley et al., 1999)
TRMI Topographic relative moisture index (Parker, 1982)
SLP Slope (degrees)
SCOSA Percent slope × cosine(aspect) transformation (Stage, 1976)
SSINA Percent slope × sine(aspect) transformation (Stage, 1976)

layer used in 2003 was mainly a function of slope and aspect, it was considered equivalent to the slope and aspect layers treated separately in the 2009 stratification. Canopy cover for the 2003 and 2009 stratifications was estimated from Landsat satellite images collected on 18 August 2002 and 25 July 2008, respectively. The mid-infrared corrected Normalized Difference Vegetation Index (NDVIC, Nemani et al., 1993) was used in 2003 and a green canopy cover fraction image derived from spectral mixture analysis using image endmembers was used in 2009. We assumed functional equivalence in these layers for purposes of stratification.

The 2003 LiDAR survey was calibrated and validated with 84 field plots (Hudak et al., 2006, 2008a), but only 76 were located within the reduced extent of the 2007 (n = 4) and 2009 (n = 72) LiDAR surveys that defined the boundary of this study. These 76 existing field plots were given priority for populating the 2009 stratification. A new private landowner denied us permission to revisit one of the 2003 plots, so only 75 plots were re-measured: 4 plots within the 2007 LiDAR survey extent in September 2008 and 71 plots within the 2009 LiDAR survey extent in June–August 2009. Because extensive harvesting activity had changed the forested landscape since 2003, 14 strata in the 2009 stratification were left unfilled by existing plots, necessitating the addition of 14 new plots. This resulted in 75 old + 14 new = 89 plots for 2007/2009 LiDAR calibration/validation. (Please note that, having now described the pertinent differences between the 2007 and 2009 LiDAR surveys, the repeat survey will be referred to as simply ‘2009’ throughout the remainder of this paper.)

Field sample plots were 0.04 ha fixed-radius plots where all trees (> 12.7 cm diameter at breast height (dbh) of 1.37 m) were tallied by species, status, dbh, and distance and azimuth from plot center. At a minimum, the largest and smallest tree by species in each plot quadrant were measured for height, height to live crown, percent live crown, and two perpendicular crown diameters. Saplings (≤ 12.7 cm dbh and > 1.37 m height) also were tallied by species in the 0.04 ha plot, and seedlings (≤ 1.37 m height) by species in a 0.002 ha subplot. Small (< 15 cm diameter) and medium (15–30 cm diameter) stumps were tallied, and large (> 30 cm diameter) stumps along with individual diameter measures, to allow estimation of tree/sapling biomass removed due to harvest disturbance. Percent cover of medium (1–2 m) and high shrubs (> 2 m) was estimated ocularly in the 0.04 ha plot, as were low shrubs, forbs, grasses, ferns, mosses/lichens, litter, and mineral soil. To measure surface fuels in 2003, four 16.1 m Brown's (1974) transects were laid in a square pattern surrounding and centered over the plot center. In 2009, two parallel 15-m Brown's (1974) transects were laid 2.5 m away from and on either side of plot center. At the ends of each 2003 transect, 1-h and 10-h fuels (i.e., fuel particles with diameters < 0.635 cm and 0.635–2.54 cm) were tallied over a 1.8-m segment while 100-h fuels (particle diameter 2.54–7.62 cm) were tallied over a 4.6 m segment. At the center of each 2009 transect, 1-h and 10-h fine fuels were tallied over a 1-m segment while 100-h fuels were tallied over a 3-m segment. In both 2003 and 2009, 1000-h fuels (i.e., coarse woody debris, CWD) were tallied along the entire transect lengths, and the diameter and decay class recorded. Litter and duff depths were also measured once at a set distance along each fuels transect.

Aboveground dry biomass of trees and saplings was calculated by species using allometric equations from Jenkins et al. (2003). Seedling biomass was not calculated. In revisited plots with stumps, aboveground

dry biomass removed from site was calculated from the stump diameter measurements, using a biomass equation generalized from Jenkins et al. (2003) across the mix of species represented in the study area. The stump diameters were downsized by a factor of 0.9 to account for the taper between the height of the stumps and breast height (Bones, 1960). Shrub and herbaceous biomasses were estimated from the percent cover measures following Smith and Brand (1983) while weighting the low, medium, and high shrub classes by their midpoint diameters of 0.5, 1.5, and 2.5 cm, respectively. Percent cover measures of forbs, grasses, ferns, and mosses/lichens were averaged and converted to biomass following Brown (1981), with a bulk density of 1.9 kg/m³ for a grass-shrub type fuelbed with a midpoint depth of 0.25 m in habitat type *P. menziesii* (Mirb.) Franco/*Physocarpus malvaceus* (Greene) Kuntz h.t.—*P. malvaceus* phase (PSME/PHMA). Surface fuels were sampled with twice the effort in 2003 than in 2009, but the different downed woody debris (DWD) transect lengths were accounted for in the volume equation of Harmon and Sexton (1996) using improved midpoint quadratic mean diameters (QMD) for the three fine woody debris (FWD) classes obtained from Woodall and Monleon (2006). DWD volumes were converted to biomass using density coefficients from Brown (1974). Litter and duff biomasses were estimated from the litter and duff depth measures following Brown et al. (1981), using a specific gravity of 25.3 kg/m³ for PSME/PHMA litter (Brown, 1981) and a specific gravity of 110.5 kg/m³ for mixed conifer forest duff (Wooldridge, 1968).

Biomass calculated for the various tree and non-tree pools was converted to carbon loads using carbon concentrations from Jain et al. (2010), which ranged from 0.379 (litter and duff) to 0.495 (tree boles). Whole tree biomass pools were multiplied by ratios of 0.8 and 0.2 to convert the boles and crowns to carbon, respectively, because the reported carbon concentrations differed. All of the aboveground carbon pools were then summed to calculate total carbon.

LiDAR canopy metrics were also computed within each 11.35 m radius inventory plot, and the topographic metrics were extracted from the 20 m topographic layers at each plot center. These 0.04 ha (400 m²) plot-level metrics constituted the reference observations for developing predictive biomass models. Note that the model and map units were the same 400 m² size to preclude scale effects.

2.4. Predictive biomass modeling

The Random Forest (RF) algorithm applied in this study for imputation was called from the *yalmpute* package (Crookston & Finley, 2008) in R (R Development Team, v2.10.0). Random Forest is a non-parametric technique that can handle both continuous and categorical independent variables and can be run in either regression mode or classification mode. The RF technique uses a bootstrap approach for achieving higher accuracies compared to traditional classification trees. RF uses the Gini statistic for node splitting which allows for non-linear variable interactions. A large number of classification trees are produced, permutations are introduced at each node, and the most common classification result is selected.

Our predictive modeling strategy was to treat each time period as an independent assessment, as a forest manager is likely to do. The 2003 and 2009 biomass models were therefore developed separately based on all available contemporaneous plot measures from either 2003 ($n = 76$) or 2009 ($n = 89$). Variable selection from the suite of 62 candidate LiDAR height, intensity, density, and topographic metrics (Table 2) was performed separately yet consistently. We ran a Random Forest model selection function that uses Model Improvement Ratio (MIR) standardized importance values (Evans & Cushman, 2009; Evans et al., 2010; Murphy et al., 2010) to objectively choose the most important LiDAR metrics for predicting the response variables. If selected predictor variables were highly correlated (Pearson's $r > 0.9$), we excluded from consideration the variable with lesser importance

according to the MIR statistic, and we repeated the model selection function to search for alternative predictors. In the interest of parsimony, a subset of influential predictors was further reduced to the ten LiDAR metrics having the greatest importance.

Following the strategy of Hudak et al. (2008a) to assign more weight to the more prevalent tree species, the three response variables included in the imputation model were total tree biomass, the biomass of the dominant species in each inventory plot, and the name of the dominant species in each inventory plot. By including tree species as a response, we could impute species-level tree biomass and not simply total tree biomass (Hudak et al., 2008a). Another advantage of imputation, besides the ability to simultaneously predict multiple responses, is that not all response variables need to be included in the neighborhood calculations to predict them. For instance in this study, we did not include the non-tree biomass or carbon pool variables in the neighborhood calculations, but imputed them nonetheless through their plot-level association to tree biomass; i.e., the understory live biomass pools were imputed as ancillary variables: saplings, shrubs, and herbaceous vegetation; as were the decomposing biomass pools: coarse and fine woody debris, litter, and duff. We also imputed habitat type (Cooper et al., 1991); the majority habitat type imputed to the map cells within each stand was used to parameterize the Forest Vegetation Simulator (FVS) projections of tree biomass from stand-level cruise data collected across the Moscow Mountain and used in this study for independent validation.

2.5. Biomass/carbon change estimation and validation

Plot-level tree biomass was imputed to the 400 m² reference plots for model validation using the root mean square difference (RMSD) and Pearson correlation statistics. The RMSD used to assess imputation model accuracy (Stage & Crookston, 2007) is analogous to the RMSE used to assess regression model accuracy. The RMSD is typically larger than the RMSE because imputed predictions preserve the variance in the observations, while regression predictions have reduced variance relative to observations. Indeed, regression predictions are unique values that can be plotted along a line, whereas imputed predictions are observations themselves. Thus, the imputed value at each plot represents the total tree biomass observed at its nearest neighbor plot (in terms of multivariate statistical distance). Predictions were also imputed to the 400 m² target cells defined by the grids of the ten LiDAR metrics included in the 2003 and 2009 models. Since the number of reference observations (i.e., plots) was so small relative to the number of target observations (i.e., individual grid cells), a systematic sample of grid cell predictor and response variables were extracted from the maps at 500 m intervals to compare the distribution of grid cell values across the landscape to the distribution of plot values designed to represent the landscape.

Fluxes of biomass and carbon were calculated over the six year time period by subtracting the 2003 maps of biomass/carbon pools from those of 2009. Positive values thus indicate net biomass/carbon gain while negative values indicate loss. Biomass change results were summarized in tabular format for harvested and non-harvested forested areas and non-forest. Non-forest was classified as areas with a DENSITY metric of zero in both 2003 and 2009; i.e., no LiDAR returns higher than breast height (1.37 m) within the 20 m × 20 m pixel. Biomass change within structural stages was estimated via overlay analysis between a map of structural stages developed for the same study area by Falkowski et al. (2009) and the change in total biomass estimated as part of this project. Structural stages mapped by Falkowski et al. (2009) followed a classification scheme developed by O'Hara et al. (1996) and included: Open—treeless areas (9 plots); Stand Initiation (si)—space reoccupied by seedlings, saplings or shrubs following a stand replacing disturbance (7 plots); Understory Reinitiation (ur)—older cohort of trees being replaced by new

individuals, broken overstory with an understory stratum present (7 plots); Young Multistory (yms)—two or more cohorts of young trees from a variety of age classes (30 plots); Mature Multistory (mms)—two or more cohorts of mature trees from a variety of ageclasses (22 plots); and Old Multistory (oms)—two or more cohorts of trees from a variety of ageclasses, dominated by large trees (6 plots). Areas with a predicted biomass decrease from 2003 to 2009 were excluded from consideration to avoid effects of human or natural disturbance on the structural stage growth estimates. Within undisturbed areas, map pixels were randomly selected to test using a one-way ANOVA whether differences in biomass increase between forest structural stages were significant. Finally, Tukey's post-hoc test was employed to evaluate which of the structural stages had experienced significant differences in biomass increase over the six year period.

We performed independent validation of 2003 and 2009 tree biomass maps using stand exam data collected from 1995 to 2010 on stands owned and managed by local forest industry ($n=502$) and the University of Idaho Experimental Forest ($n=620$). The monthly cruise dates were generalized using the 'Inland Empire' variant of FVS and an annual time step. Dates on or before 30 June were considered prior year inventory, and dates on or after 1 July were considered current year inventory. Tree diameter growth was projected forward in annual diameter increments from the inventory year until the projection years of 2003 and 2009, to validate the 2003 and 2009 LiDAR predictions. A substantial number of industry stands were inventoried in 2010 ($n=209$), so in these cases a single annual diameter increment was subtracted to obtain a 2009 projection. (There were also a few inventoried industry stands ($n=22$) that were either wholly or mostly located within the 2007 LiDAR survey; in these cases tree growth was projected until 2007 instead of 2009.) Individual tree biomass calculated by species per Jenkins et al. (2003) and projected tree density from FVS were multiplied to estimate projected tree biomass per unit area in the same units as predicted tree biomass (Mg/ha).

Total and species-level tree biomass predictions were summarized at the stand level using the zonalstats utility in ArcGIS. Zonal means of the total tree biomass predictions were differenced (2009–2003) to define a biomass change threshold in terms of harvest disturbance. Besides the visually evident patterns of harvest in relation to the stand maps, private industry also provided maps of harvest units that were helpful in defining a harvest threshold from the distribution of calculated biomass change values. Zonal sums of the 2003 and 2009 tree biomass predictions were compared to FVS individual tree biomass projected to 2003 and 2009 and summed within each stand. Zonal sums of the non-tree 2003 and 2009 predicted biomass/carbon pools were also generated from the maps. Stands classified as harvested were excluded from the 2009 predicted tree biomass map validation because the stand exam data projected to 2009 did not account for harvest. (The harvest unit polygons provided by local industry partners did not include tree data and were not the same as the industry stand map polygons that did.)

Following Hudak et al. (2008b), the null hypotheses of dissimilarity concerning the *bias* and *proportionality* of LiDAR-derived tree biomass predictions compared to traditional stand exam derived tree biomass projections were tested using the equivalence package (Robinson et al., 2005) in R. Sapling biomass predictions were added to the tree biomass predictions because the tree biomass projections included saplings. The equivalence test regresses observations on predictions in a simple linear regression and bootstraps the data to test whether the intercept (a measure of *bias*) and slope (a measure of *proportionality*) terms are dissimilar. Rejection of the null hypothesis of dissimilarity provides evidence, and confidence intervals, that the intercept and slope terms are biased and disproportionate, respectively. Significance reported throughout his paper corresponds to an alpha level of 0.05.

3. Results

3.1. Predicted biomass and estimated biomass change

Mean canopy height was the most important LiDAR metric for predicting tree biomass in both 2003 and 2009. Mean height was followed by several other height, density, intensity, or topographic metrics (Fig. 4) selected from the suite of candidate predictor variables (Table 2) that were not highly correlated ($r<0.9$). The full count of available reference plots was used to develop the independent tree biomass models, with slightly higher imputation accuracy in 2003 (RMSE=92.75 Mg/ha of aboveground biomass) than in 2009 (RMSE=101.87 Mg/ha of aboveground biomass) (Fig. 5). Only 75 plots common to both field surveys were available for estimating 2003 to 2009 tree biomass change at the plot level (Fig. 6). Subtracting predicted plot-level tree aboveground biomass in 2003 from 2009

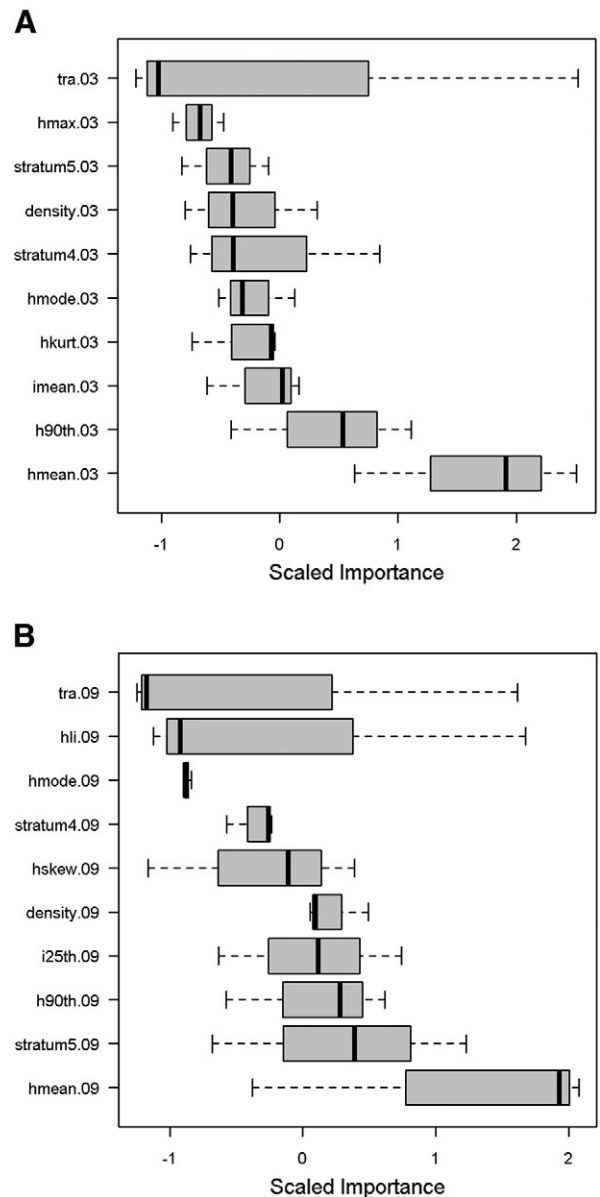


Fig. 4. Random Forest dimensionless variable importance measures that have been scaled to have an overall mean of zero across 1000 classification trees to impute aboveground tree biomass in A) 2003 and B) 2009. Thick black lines indicate medians, gray boxes interquartile ranges, and whiskers full ranges. Abbreviations of the ten selected LiDAR metrics shown on the y axis, sorted with most important metrics at the bottom, are defined in Table 2.

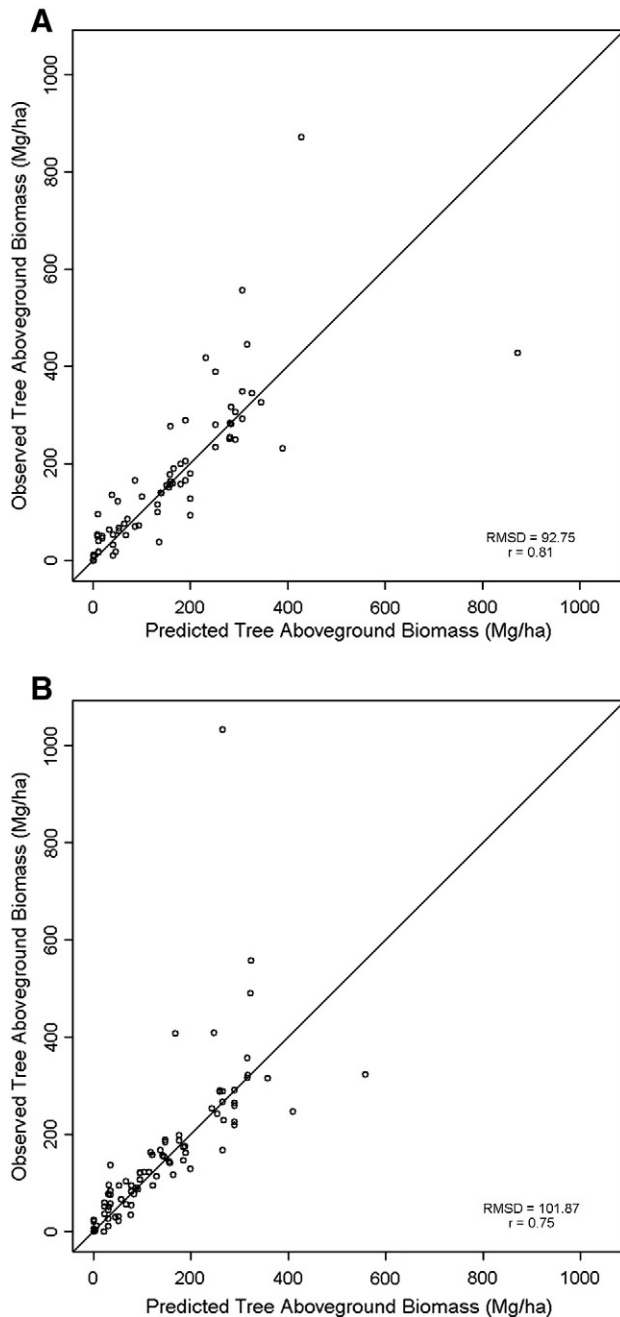


Fig. 5. Predicted versus observed tree aboveground biomass at field plots in A) 2003 ($n = 76$) and B) 2009 ($n = 89$) based on 1000 classification trees of Random Forest imputation. The solid diagonal line is the 1:1 line. Pearson correlations are highly significant ($p < 0.0001$).

provided plot-level estimates of biomass change that were more variable than the independent 2003 and 2009 predictions (Fig. 5), yet were still significantly correlated (Fig. 6). Field crew calls of “disturbed” at 20 plots did not reveal the magnitude of the disturbance, so a conservative harvest threshold of -66 Mg/ha was defined in deference to the greater confidence in the “undisturbed” plot calls (Fig. 6). This -66 Mg/ha threshold for defining harvest disturbance was corroborated by our stand-level validation (detailed in the next section below).

Predictions of the non-tree biomass pools were imputed as ancillary variables to the tree biomass models; non-parametric Wilcoxon signed rank tests of predicted versus observed non-tree biomass pools (Fig. 7) did not significantly differ in any cases in either 2003 or 2009 ($p > 0.13$). Wilcoxon signed rank tests of predicted vs. observed tree biomass

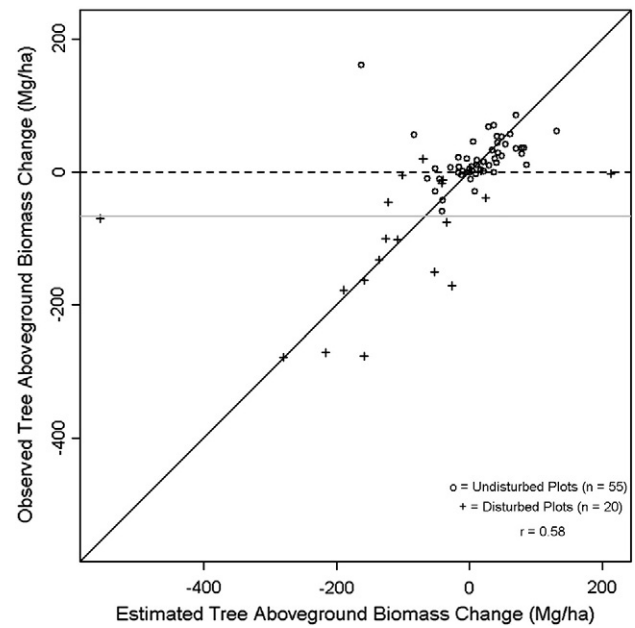


Fig. 6. Estimated vs observed tree aboveground biomass change from 2003 to 2009 at the revisited field plots ($n = 75$). The solid diagonal line is the 1:1 line, the horizontal dashed line is the zero observed tree biomass change line, and the horizontal gray line is the conservatively selected observed tree biomass change threshold (-66 Mg/ha) below which disturbed units were considered harvested. Pearson correlation is highly significant ($p < 0.0001$).

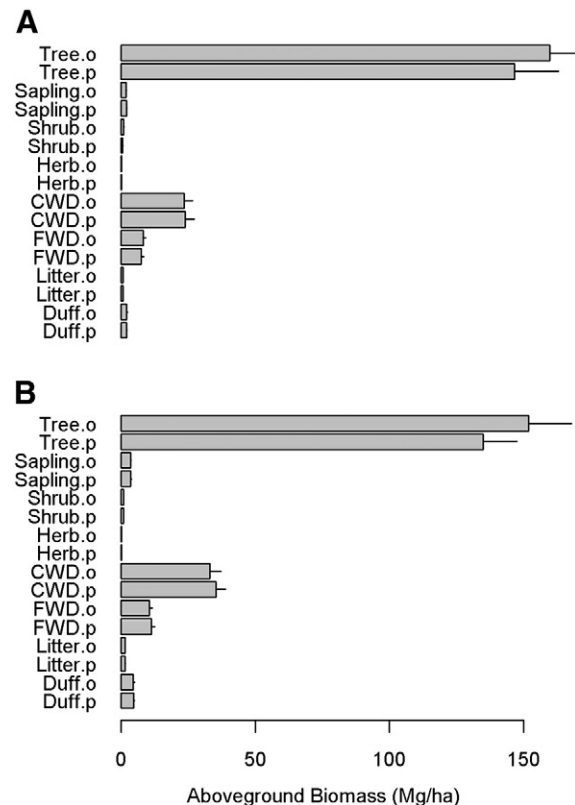


Fig. 7. Mean ($\pm$ SE) predicted (“p”) and observed (“o”) aboveground biomass pools imputed at the field plots across 1000 Random Forest classification trees in A) 2003 ($n = 76$) and B) 2009 ($n = 89$). Non-parametric Wilcoxon signed rank tests showed that none of the observed vs. predicted aboveground biomass pools significantly differed ($p > 0.05$).

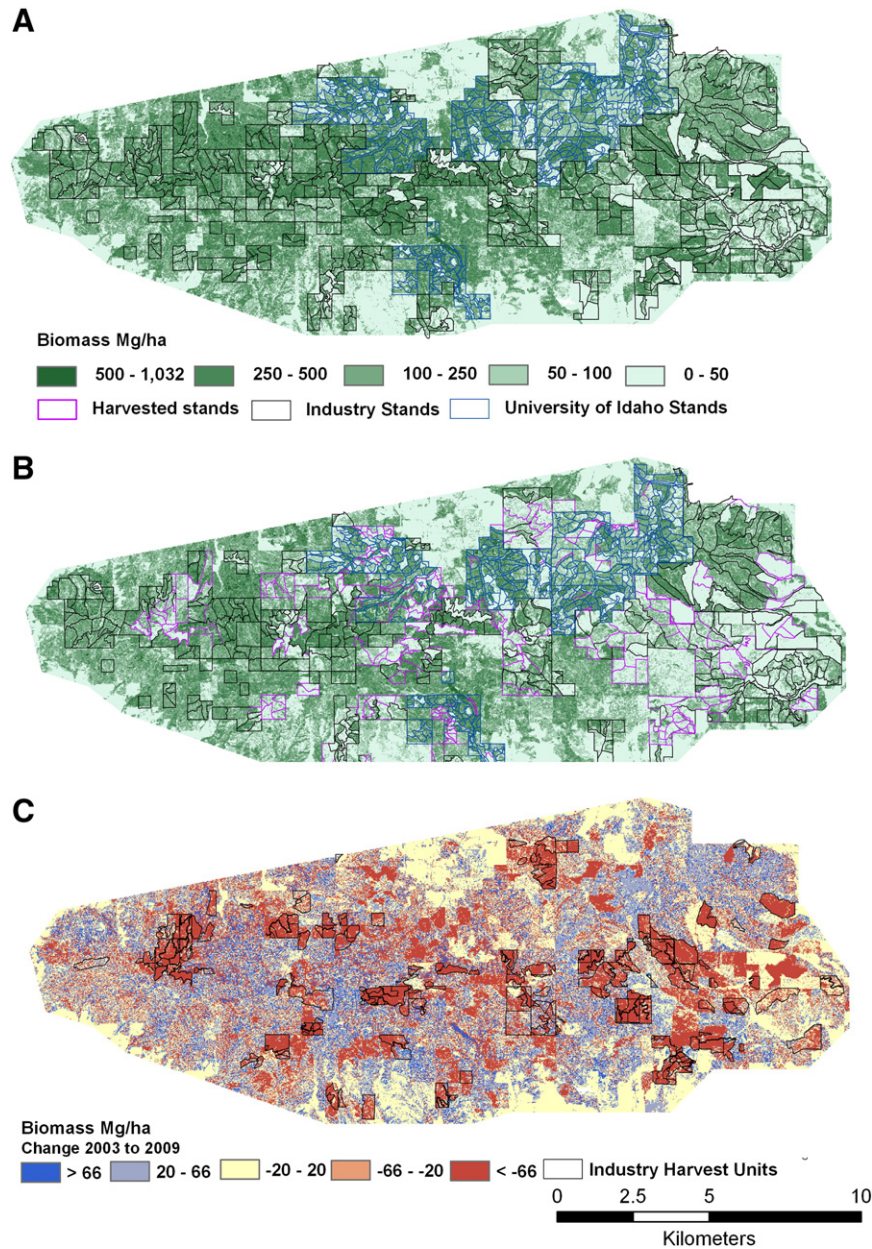


Fig. 8. Predicted tree aboveground biomass across the study area in A) 2003 and B) 2009, and C) estimated tree aboveground biomass change produced by subtracting A) from B).

were closest to significant, with predictions being slightly less than observations in both 2003 ($p = 0.063$) and 2009 ($p = 0.062$) (Fig. 7).

Landscape-wide predictions of the various biomass and carbon pools were mapped at a $20\text{ m} \times 20\text{ m}$ pixel resolution based on the 2003 and 2009 tree biomass models (Fig. 8). The 2003 tree biomass map (Fig. 8A) was subtracted from the 2009 tree biomass map (Fig. 8B) to estimate tree biomass change (Fig. 8C). Removed from consideration were non-forested agricultural areas classified from

the LiDAR as having zero canopy density in both 2003 and 2009, amounting to 6.2% of the landscape, found mostly around the periphery of the study area (Table 3). Harvested areas comprised 26.3% of the study area and were defined as having lost at least 66 Mg/ha of aboveground tree biomass, which translates into a landscape-wide mean annual harvest rate of -32.3 Mg/ha/yr (Table 3). Meanwhile, annual tree biomass growth in unharvested areas of the landscape (67.5%) over six years averaged 4.1 Mg/ha/yr . Mean annual rates of total aboveground carbon sequestration varied from 2.8 Mg/ha/yr in

Table 3

Landscape-level summary of 2003–2009 changes in aboveground biomass pools.

	Hectares	Percent of landscape	Tree aboveground biomass change (Mg/ha/yr)	Total aboveground carbon change (Mg/ha/yr)
Non-harvested	13,919	67.5%	4.1	2.8
Harvested	5,417	26.3%	-32.3	-16.5
Non-forest	1,288	6.2%	0.2^a	0.5
Total	20,624	100.0%	-5.7	-2.3

^a Theoretically should be zero, so this is an indication of the map uncertainty.

unharvested lands to -16.5 Mg/ha/yr in harvested lands, or -2.3 Mg/ha/yr overall; thus, the intensive and extensive harvest activities across the Moscow Mountain study area resulted in an overall loss in aboveground carbon from the landscape over the 6-year study period (Table 3).

Closer examination of the most important predictor variable in both the 2003 and 2009 models, mean canopy height, reveals a linear relationship to predicted 2003 or 2009 tree biomass, or estimated 2003 to 2009 tree biomass change; simple linear regression models based on mean canopy height explain significant proportions of variance in these response variables whether compared at the plot or landscape levels (Fig. 9). In contrast, the relationship of the same tree biomass or biomass change variables to either maximum canopy height or canopy density (not shown) is curvilinear and more scattered.

3.2. Biomass change assessment and validation

The $20 \text{ m} \times 20 \text{ m}$ mapped pixels of biomass change (Fig. 8C) were tested for spatial autocorrelation; autocorrelation was determined to be 8% at 20 m, 2% at 40 m, and 0% at longer lag distances. Given the spatial dependence between neighboring pixels, a random sample of 27,034 (10%) of the 20 m mapped pixels of biomass increase were compared between the six structural stages mapped by Falkowski et al. (2009). Analysis of variance confirmed that there was an overall difference in biomass increase across the six structural stages evaluated in this study ($F = 665$, $p < 0.0001$). Using a random sample assured that the ANOVA's underlying assumption of independent observations was not violated. We found that in this system the longer the time since disturbance, the greater the accumulation of aboveground biomass over the 6-year study period (Fig. 10). Biomass

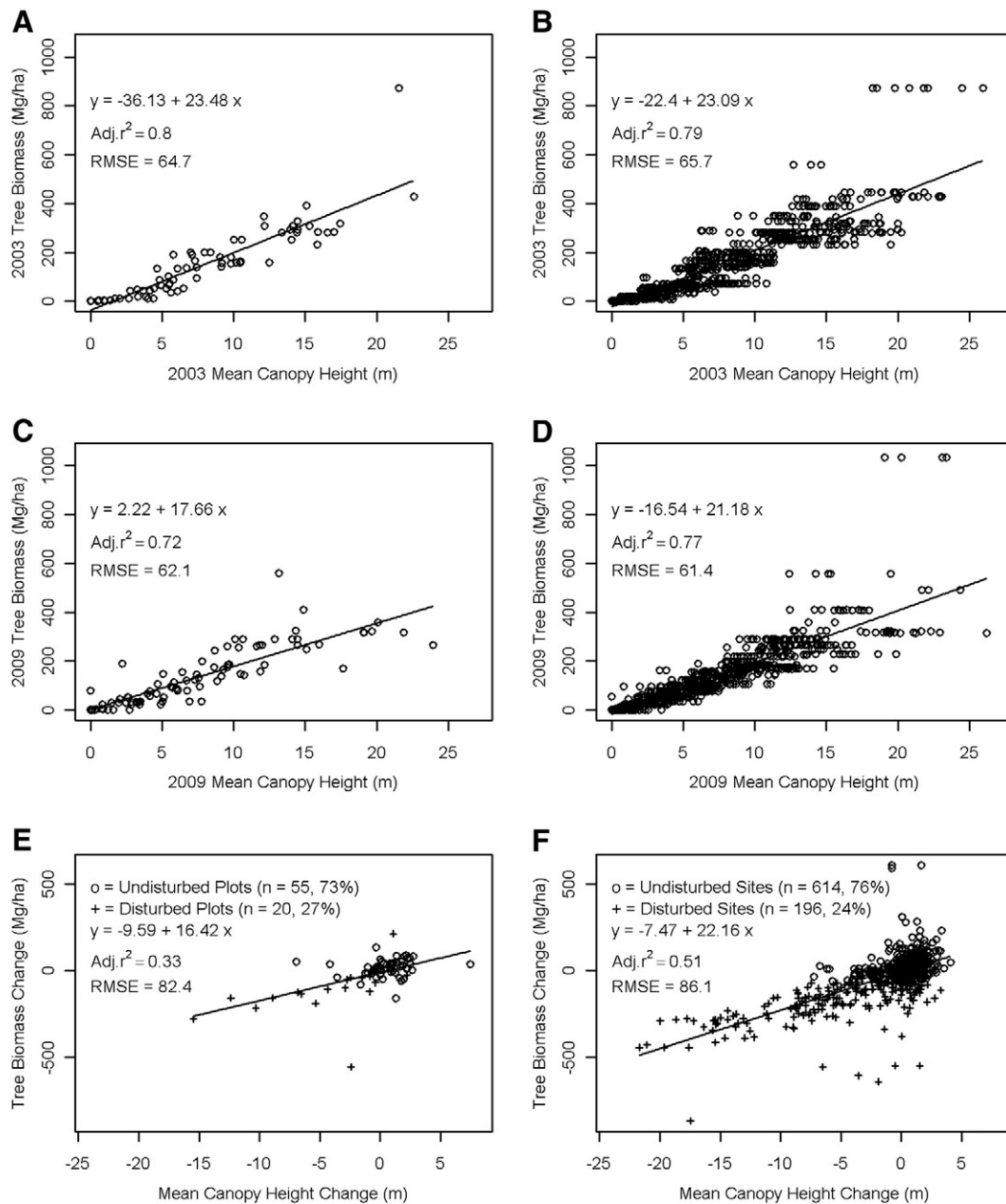


Fig. 9. Relationship of imputed tree aboveground biomass to mean canopy height at the A) 2003 field plots ($n = 76$); B) 2003 imputed tree aboveground biomass map sampled at 500 m intervals; C) 2009 field plots ($n = 89$); D) 2009 imputed tree aboveground biomass map sampled at 500 m intervals. Relationship of imputed tree aboveground biomass change to mean canopy height change (2003–2009) at the E) revisited field plots ($n = 75$) and F) 2003–2009 tree aboveground biomass change map sampled at 500 m intervals ($n = 810$). All Pearson correlations are highly significant ($p < 0.0001$).

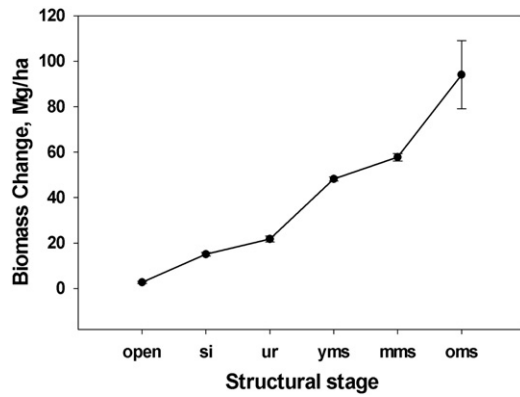


Fig. 10. Above ground woody biomass change within previously mapped structural stages (Falkowski et al., 2009). Open; Stand Initiation (si); Understory Reinitiation (ur); Young Multistory (yms); Mature Multistory (mms); and Old Multistory (oms). The error bars indicate the 95% confidence intervals. Overall, the biomass change between structural stages significantly differs ($p < 0.0001$). All pairwise differences are significant ($p < 0.0001$).

accumulation was significantly different between all six structural stages ($p < 0.0001$).

Stand-level tree and sapling aboveground biomass predictions summarized via LiDAR were compared to stand-level cruise data projected in FVS to the time of the 2003 and 2009 surveys, using equivalence plots that graphically illustrate bias and disproportionality (Fig. 11). In terms of bias, equivalence plots showed that the predictions were significantly similar to the projections in both years. In terms of disproportionality, equivalence plots showed disproportionality to be significant in 2003 and almost significant in 2009.

The predicted biomass change distributions within stands classified as harvested were very similar to predicted biomass change distributions within harvest units supplied by our industry partners (Fig. 12); the mean change between 2003 and 2009 biomass predicted in the classified industry harvest stands was -167.0 ($SE = 5.2$) Mg/ha, while in the industry harvest units it was -173.3 ($SE = 7.8$) Mg/ha. Note that the harvest unit polygons supplied by our industry partners (Fig. 8C) were not the same as the stand map polygons (Fig. 8A, B).

Having established from both the plot-level and stand-level analysis the validity of the -66 Mg/ha threshold of minimum biomass change due to harvest, we explored predictive maps of the non-tree biomass pools that also were summarized at the stand level. Industry-based stand exam data lacked information for these variables, but we could assess whether estimated changes in non-tree biomass pools were reasonable given expectations and observations about the effects of harvest activities. For instance, after at most 6 years following harvest in this study, seedlings would only be starting to reach sapling size, and regenerating stands would be shrub-dominated. Furthermore, activity fuels are typically broadcast burned or piled and burned on Moscow Mountain, both of which reduce CWD loads. Conforming to these expectations, Fig. 13 illustrates observed significant trends in predicted sapling, shrub, CWD, litter and duff (latter two not shown) biomass pools as a function of harvest impact. Expected tree biomass exported off site, calculated from stump tallies, also showed a significant trend in harvested stands (Fig. 13). There were no discernible trends in the non-tree biomass pools in non-harvested stands.

4. Discussion

4.1. Opportunities and challenges concerning repeated measures

The repeat surveys were independent assessments and our analysis strategy was to treat them as such. Forest managers are similarly likely to be faced with multi-temporal datasets that differ in certain

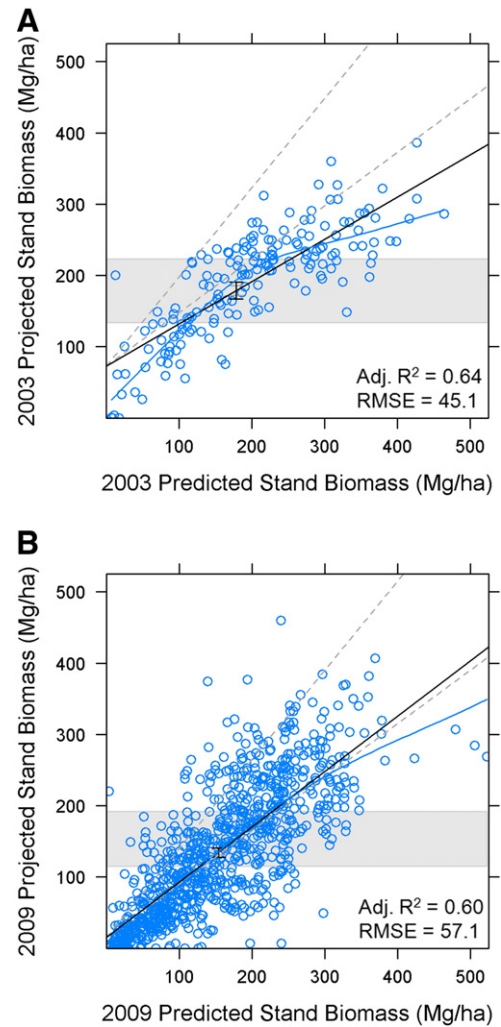


Fig. 11. Relationship of tree and sapling biomass predicted from LiDAR versus from independent stand exam data projected and expanded to the same stands in A) 2003 ($n = 174$) and B) 2009 ($n = 881$, non-harvested stands only). The black line indicates the line of best fit and the blue line the loess smooth. The gray shaded bar defines the region of similarity in the intercept, indicated with a gray confidence interval where the predicted and observed (projected, in this case) data means intersect. If the gray confidence interval falls within the gray region of similarity, then the predictions are statistically unbiased with respect to the observations (projections). The dotted diagonal lines define the region of similarity in the slope, indicated with a black confidence interval atop the gray confidence interval. If the black confidence interval falls within the dotted gray lines, then the predictions are statistically proportional with respect to the observations (projections). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

regards (e.g., LiDAR pulse density), but that are on the whole very similar, and therefore appealing to exploit to meet practical objectives for forest inventory and monitoring (Hudak et al., 2009; Wulder et al., 2008). We included the small 2007 LiDAR and 2008 field plot datasets in this study because forest managers responsible for forest inventory and planning often must reconcile data collections with different dates to maximize coverage for minimal cost. The methods demonstrated in this paper should prove helpful for others attempting to conduct a biomass/carbon change assessment via repeat surveys after considering four important points.

First, LiDAR sensor capabilities are advancing rapidly. The 30-fold mean difference in point densities between the 2003 and 2009 LiDAR surveys did not affect our biomass estimates at the plot level, because the distribution of canopy heights was stable (Fig. 3). Although exactly consistent acquisition parameters were not the case in this study (Table 1), the three LiDAR datasets were sufficiently

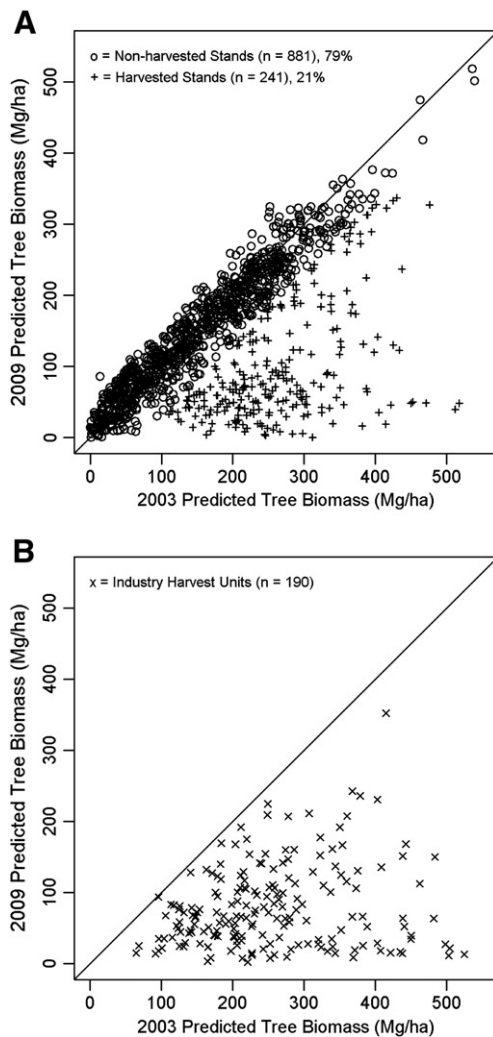


Fig. 12. Relationship of imputed tree aboveground biomass in 2003 and 2009 in A) stands classified as non-harvested or harvested (Fig. 8B) compared to B) 2003–2009 industry harvest units (Fig. 8C); i.e., industry harvest units in B) are not the same as harvested stands in A).

comparable when aggregated to the 400 m² scale. The 0.4 points/m² mean point density of the 2003 survey translates to a mean of 160 points per 0.25-ha (400 m²) plot, which is a sufficient number of points to produce a stable canopy height distribution from which to calculate canopy height metrics. Maximum canopy height may be a less reliable metric to compare between repeat LiDAR surveys; for instance, the higher LiDAR pulse density in 2009 compared to 2003 would translate into less height underestimation bias in 2009 than in 2003, whereas mean canopy height would be less subject to such a bias. The mean of 4790 points per plot collected in 2009 represents over-sampling at the plot level of aggregation. Such high density LiDAR can permit individual tree characterization under open canopy conditions but not easily or accurately in closed canopies like on much of Moscow Mountain (Falkowski et al., 2006, 2008).

Second, it is important that the calibration/validation plots represent forest conditions across the landscape in a representative and unbiased manner. The repeat LiDAR coverage was of smaller extent than the 2003 LiDAR coverage, affecting the landscape stratification. Six of the eight 2003 plots located exterior to the repeat LiDAR surveys were non-forested plots, making their exclusion from the 2003 model inconsequential. However, the high degree of change due to harvest activity within the study landscape required the addition of

14 new plots to populate the re-stratification. Our results support the idea that forest inventory plots used to develop predictive biomass models need not be exactly the same to produce comparable results between repeat inventories. Representative sampling can be accomplished through random or random stratified sampling designs conditioned on the spatial extent of the landscape they represent, or systematic monitoring plots as used by the USFS Forest Inventory and Analysis program (FIA). The coarse spatial frequency of FIA plots relative to this and most other LiDAR project areas requires more intensive localized sampling to adequately characterize the range of variability in forest structure conditions. Upscaling of plot-level biomass data into wall-to-wall maps as demonstrated by this study could be replicated at regional or even national scales using FIA plot data as broader LiDAR coverage becomes available (Stoker et al., 2008; Vierling et al., 2011). Such LiDAR data products need not necessarily be spatially contiguous but could be developed via integration between distributed LiDAR sample data and contiguous Landsat or other satellite imagery (Hudak et al., 2002).

Third, our inventory plots were not originally established for high-precision repeat monitoring. Although 75 of the field plots established in 2003 were re-measured in 2009, they had not been marked with permanent monuments in 2003. The 2009 field crews navigated to and placed the 2009 plot centers as closely as possible to the unmarked 2003 plot center locations. Despite the fact that both the 2003 and 2009 plot centers were geolocated with differential GPS, differences between 2003 and 2009 plot locations vary from 0.46 m to 9.25 m with a mean of 2.67 m and a standard deviation of 1.65 m. These offsets do not include the additive uncertainties in the 2003 and 2009 plot locations. We expected the geolocation errors to contribute greatly to the scatter in the biomass change estimates illustrated in Fig. 6. However, when we tested the effect of the geolocation offsets on overall error in estimated biomass change in the 55 non-harvested plots, by regressing 2009 biomass observations on 2003 biomass observations in a simple linear regression model ($y = 1.07x + 9.39$, RMSE = 32.7 Mg/ha, Adj. $r^2 = 0.96$, $p < 0.0001$) and then comparing the residuals against the offsets calculated between the 2003 and 2009 recorded plot center locations, we found no relationship ($r = -0.01$, $p = 0.94$). This suggests that 2003 and 2009 imputation model errors and pure error (Stage & Crookston, 2007) may be larger contributors to the overall errors in predicted biomass than inconsistencies in plot location between the field sampling periods. These additive errors are cumulative when summed across repeated measurements, and should contribute to higher variance in biomass change predictions than biomass predictions confined to a single time. This is a major reason we developed independent 2003 and 2009 biomass models in this study, and compared the independent predictions to estimate biomass change, rather than predict biomass change directly.

Fourth, the importance of using consistent techniques to measure biomass in the field plots cannot be overstated. Changes in sampling protocol or field crew personnel can create biases that can complicate comparisons of repeated measurements. For instance, the non-tree biomass components were sampled using slightly different protocols and different field crews in 2009 than in 2003, which could reduce the comparability of these pools between the two repeat inventories (Fig. 7). This was an argument for basing the predictive models on just the trees, which were consistently measured, and to which LiDAR can be expected to be sensitive. Minimizing any measurement biases in the non-tree components between 2003 and 2009 was yet another argument for developing the 2003 and 2009 models independently.

4.2. Tree, plot, pixel, stand, and landscape level inferences

The high spatial resolution of LiDAR makes pixel-level maps and field characterization of accurately geolocated inventory plots at

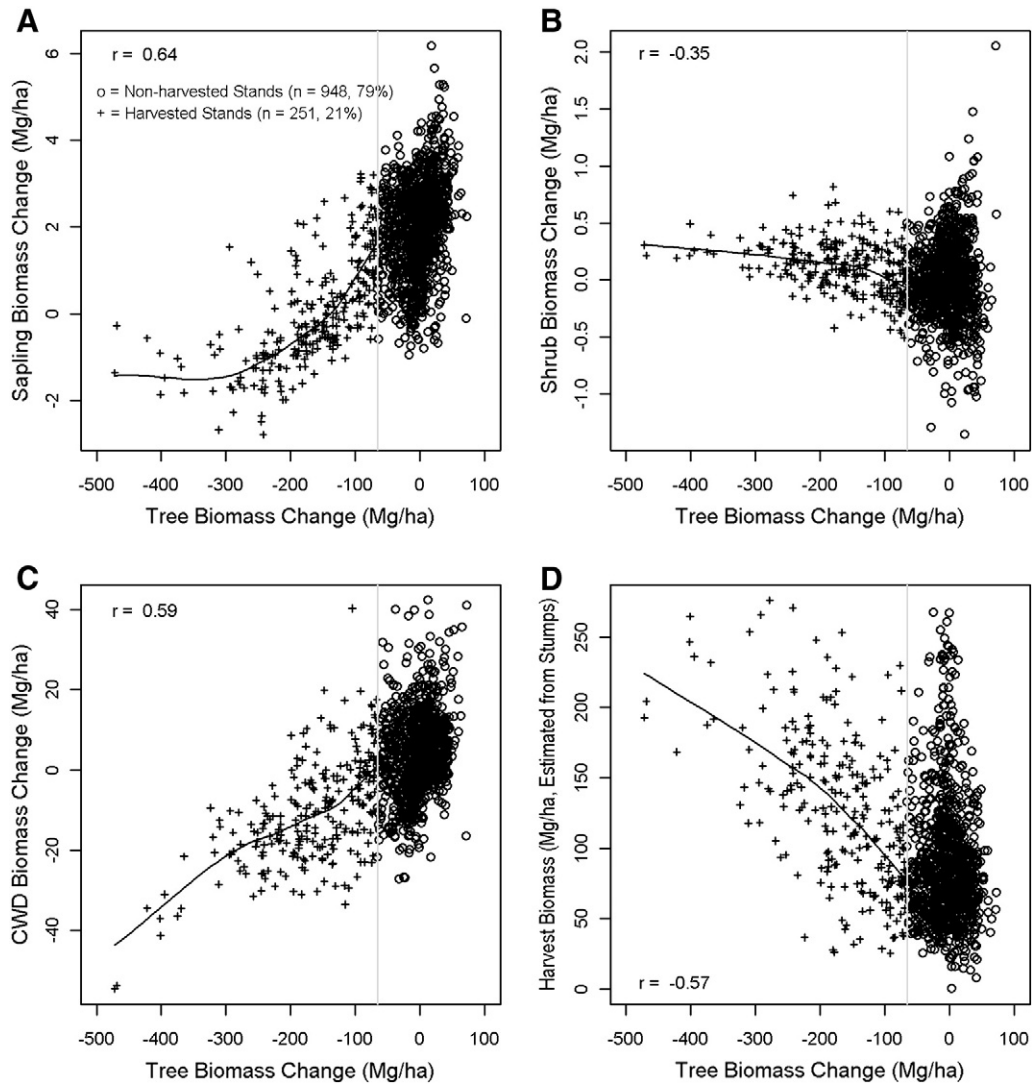


Fig. 13. Stand-level tree aboveground biomass change versus biomass change in A) saplings, B) shrubs, C) coarse woody debris (CWD), and D) harvested trees, as estimated from stumpage. The vertical gray lines are the conservatively selected observed tree aboveground biomass change threshold (-66 Mg/ha) below which disturbed units were considered harvested. The black lines are the loess trends fit to the harvested stands only. Pearson correlations are all highly significant ($p < 0.0001$).

least as accurate and cost effective as traditional inventories focused at the stand level (Hummel et al., 2011). Most forest inventory data used by forest managers is collected at the stand level, and forest stands represent the operational units for implementing management decisions. However, developing predictive models from tree measurements collected in geolocated inventory plots is much more efficient than traditional stand exams. Indeed, 2393 trees were tallied in the repeat field plot inventory, while 32,183 trees were tallied in the industry stands and 17,740 trees were tallied in the University of Idaho Experimental Forest stands—a combined 20-fold difference in fieldwork effort. Furthermore, pixel-level predictive maps provide added utility to forest managers because they can be aggregated to different management units or as stand maps change. Much of the high variability in predictions that contributes to poor accuracy at the pixel level gets averaged out upon aggregation to the stand level at which management decisions are made. For instance in this study, the high RMSE of 93–102 Mg/ha at the plot level (Fig. 5) is halved to an RMSE of 45–57 Mg/ha at the stand level (Fig. 11). At the resolution of individual (400 m^2) plots or pixels, RMSEs of simple linear regression models of tree aboveground biomass based on mean canopy height alone ranged from 61 to 66 Mg/ha; simple linear regression models with the added temporal uncertainty of biomass change increased RMSEs to 82–86 Mg/ha (Fig. 9). Tree aboveground biomass was linearly

related to mean canopy height because nearly the entire study landscape is composed of secondary growth forest in which height growth has not yet reached an asymptote. The high biomass outliers in Fig. 9 are imputations of the single old growth stand surveyed; these provide an indication that a greater presence of older age structures would introduce nonlinearity into the relationship.

Regression model RMSE is typically lower than imputation model RMSE, especially when only a single nearest neighbor is imputed, as in this study. The RMSEs reported at the plot level (Fig. 5) are ~10% higher than RMSE statistics from comparable RF models run in regression mode in a preliminary analysis (Vierling et al., 2010). In other words, using RF in regression mode produced higher local accuracy but at the cost of reduced global accuracy. For instance, the highest tree biomass observed was at a single old-growth plot, so the imputed nearest neighbor value for this plot is unavoidably much smaller, which inflates the RMSE (Fig. 5). The use of regression predictions may be problematic for landscape-level carbon accounting, because regression predictions have reduced variance relative to observations, while imputed predictions using a single nearest neighbor preserves the variance in observations. As the number of k -nearest neighbors increases, the result approaches the regression solution (Eskelson et al., 2009; McRoberts et al., 2002; Tuominen et al., 2003), given a sufficient number of well geolocated and distributed

plots (Falkowski et al., 2010; Hudak et al., 2008a,b). Less variance in the 2003 and 2009 RF regression model predictions means they were shifted towards the mean, resulting in an underestimation of biomass/carbon change in both unharvested and harvested forest at the landscape level (Vierling et al., 2010).

In this paper, equivalence plots of predicted and projected stand-level biomass in 2003 and 2009 indicated that the means were statistically similar but that there was disproportionality that was significant in 2003 (Fig. 11). Upon further exploration, we found that the disproportionate slope term between predicted and projected stand-level biomass was a function of cruise data inventory year. Cruise data more than six years old tended to come from the higher biomass stands and constituted a higher proportion of the 2003 validation (72% from 1997 or earlier) than the 2009 validation (18% from 2003 or earlier). This had the effect of pulling down the linear trendline of best fit in both validations, but especially in 2003 (Fig. 11). It may be that the FVS Inland Empire variant predicts growth too conservatively compared to the true growth rate on Moscow Mountain, because tree aboveground biomass gain due to growth was projected to be 3.6 Mg/ha/yr versus 4.1 Mg/ha/yr as estimated from LiDAR (Table 3).

Some of the trees within the 75 revisited plots were measured for height in both field inventories. The mean annual height growth estimated from these trees ($n=287$) was 0.4 m/yr ($\sigma=0.8$ m/yr), matching the mean plot-level height growth rate of 0.4 m/yr ($\sigma=0.5$ m/yr) reported by Hopkinson et al. (2008) in a mature red pine plantation in southeastern Ontario. Based on maximum LiDAR height measures from four repeat LiDAR surveys spanning five years, Hopkinson et al. (2008) estimated plot-level height growth of 0.38 m/yr (2000–2002), 0.29 m/yr (2002–2004), 0.38 m/yr (2004–2005), and 0.34 m/yr overall (2000–2005). This also matches our own estimates of pixel-level height growth from LiDAR maximum height measures within the 146 ha unharvested area where the 2003, 2007, and 2009 LiDAR surveys overlapped: 0.36 m/yr (2003–2007), 0.32 m/yr (2007–2009), and 0.34 m/yr (2003–2009) overall. It is also noteworthy that our study corroborates a widely reported, slight but consistent LiDAR canopy height underestimation bias (Hopkinson et al., 2008; Lim et al., 2003). This likely explains why our plot-level tree aboveground biomass predictions were slightly lower than observations in both 2003 and 2009 (Fig. 7).

4.3. Biomass gains by structural stage and implications for forest management

Assessing biomass accumulation over large areas and extended time periods is essential for improving estimates of carbon pools and fluxes and potential effects on regional- to global-scale carbon budgets (e.g. DeFries et al., 2002; Houghton et al., 2009; Pan et al., 2011; Strand et al., 2008). For example, forest stand age and rates of ecosystem carbon exchange often exhibit a non-linear relationship, which differs according to species or climate. Law et al. (2003) recorded differences in carbon accumulation rates along a forest chronosequence created by differently aged clearcuts in ponderosa pine, and Van Tuyl et al. (2005) extended this work to estimate forest net primary productivity (NPP) and carbon storage across broader precipitation, elevation, disturbance, and species gradients in Oregon. Young regenerating stands exhibited negative NPP values in all cases due to respiration exceeding photosynthesis, while older stands reached maximum NPP values at different stand ages (i.e., max NPP in moist productive forests occurred in stands <30 years old, whereas maximum rates in dry forests occurred at a stand age >100 years old). Similarly, Schwalm et al. (2007) recorded carbon loss in young stands (<20 years) followed by an increased ecosystem NPP with increased stand age in Douglas-fir in British Columbia. Although structural stages are not necessarily related to stand age, we found that structural stages containing mature and old trees stored two to

three times more carbon over the six year time period than did stands composed of younger trees (Fig. 10).

The majority of the study area is managed for timber production and harvest has occurred in virtually all stands within the past century. Therefore, we did not expect to find a decrease in aboveground biomass accumulation for any structural stages, even those dominated by large trees (after Law et al., 2003; Fig. 10). This finding has implications for forest management, as implementing longer harvest rotations across the study area would likely favor increased carbon uptake at the stand scale, resulting in a landscape-wide increase in aboveground carbon storage through time. As a result, a shift in forest management that would account for the value of standing carbon pools as a function of stand age (e.g. for mitigating atmospheric CO₂ emissions), in addition to the value of merchantable timber, may lead to longer harvest rotations in this landscape.

LiDAR is most sensitive to forest attributes related to tree heights (Wulder et al., 2008), yet the imputation modeling approach as we have demonstrated here allows for simultaneous prediction of other biomass/carbon pools besides just the trees (Fig. 7), providing a more comprehensive ecosystem accounting of growth and harvest impacts (Figs. 12–13). We note that to understand the true tradeoffs in carbon storage with a shift towards a longer harvest management regime, a life cycle analysis of the forest products created by harvest (e.g., the carbon released and stored via the production, transport, and use of lumber) also should be taken into account (e.g., Pan et al., 2011; Skog & Nicholson, 1998). The carbon accounting tool of the Forest Vegetation Simulator is available for this task (Hoover & Rebasin, 2008), as is a more recent capability to project growth and carbon sequestration under alternative climate scenarios (i.e., Climate-FVS; Crookston et al., 2010). As this study illustrates, trees grow and sequester carbon slowly compared to how quickly harvest can deplete carbon stores. Future work with this dataset that involves stand growth modeling and post-harvest carbon-related life cycle analyses would likely provide useful predictions for determining optimal management/harvest cycles for carbon sequestration in this area. Further combining these predictions with ground- and LiDAR-based estimates of biodiversity in this area (e.g., Martinuzzi et al., 2009; Vierling et al., 2008; Vogeler et al., in review) would yield a more holistic picture of the ecological implications of changing harvest regimes.

5. Conclusion

In this study, we demonstrate the utility of using repeat discrete return airborne LiDAR surveys in concert with field sampling and statistical modeling techniques to quantify spatiotemporal patterns of aboveground biomass change and carbon flux in a heavily managed conifer forest. We found Moscow Mountain to be a net carbon source to the atmosphere during this limited period. Our biomass predictions and estimates of biomass change and carbon flux are strictly empirically derived and are limited to the spatial extent of Moscow Mountain and the temporal window of six years. Nevertheless, this forest is representative of many forests around the globe in that it is managed by multiple user groups, including industrial forestry companies, private owners, and public land managers. The results of this study indicate that multi-temporal LiDAR may be used to monitor biomass change and carbon flux across large tracts of actively managed forested land.

Forest managers may also want to follow our sampling strategy, because ongoing harvests and other disturbances will alter the population sampled across the landscape. If the landscape changes due to widespread disturbance, so too would the canopy conditions upon which the landscape-level stratification is partially based. While a permanent plot monitoring strategy may be advised for some applications, such as detecting climate change effects, re-stratification of the landscape may be the more practical and effective strategy for

repeated biomass inventories of actively managed landscapes such as Moscow Mountain. Projecting future forest carbon sequestration and potential species shifts under alternative climate and management scenarios would be a valuable exercise for project planning. As LiDAR data become continually more available across a range of biomes, we expect that the approach outlined in this paper will assist with quantifying aboveground forest carbon pools and fluxes and therefore support current and future efforts to mitigate increasing levels of atmospheric CO₂.

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