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Development of height-volume relationships in second growth *Abies grandis* for use with aerial LiDAR

Research Note for Canadian Journal of Remote Sensing, Special Issue: Advanced Forest Inventory

Wade T. Tinkham^{a‡}, Alistair M.S. Smith^b, David L.R. Affleck^c, Jarred D. Saralecos^c, Michael J. Falkowski^d, Chad M. Hoffman^a, Andrew T. Hudak^e, and Michael A. Wulder^f

^a Forest and Rangeland Stewardship, Colorado State University, Fort Collins, Colorado, 80523-1472, USA; Wade.Tinkham@colostate.edu, M.Falkowski@colostate.edu, C.Hoffman@colostate.edu

^b Department of Forest, Rangeland, and Fire Sciences, University of Idaho, Moscow, Idaho, 83844, USA; alistair@uidaho.edu

^c Department of Forest Management, University of Montana, Missoula, Montana, 59812, USA; david.affleck@umontana.edu, jarred.saralecos@umconnect.umt.edu

^d Rocky Mountain Research Station, U.S. Forest Service, Moscow, Idaho, 83843, USA; ahudak@fs.fed.us

^f Canadian Forest Service (Pacific Forestry Centre), Natural Resources Canada, Victoria, British Columbia, V8Z 1M5, Canada

[‡] Corresponding author email: Wade.Tinkham@colostate.edu

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Abstract

Following typical forest inventory protocols, individual tree volume estimates are generally derived via diameter-at-breast-height (DBH) based allometry. Although effective, measurement of DBH remains time consuming and potentially a costly element in forest inventories. The capacity of airborne light detection and ranging (LiDAR) to provide individual tree-level information poses options for estimating tree-level attributes to enhance the information content of forest inventories. LiDAR provides excellent height measurements and given the physiologic scaling connection of plant height and volume; using individual tree height-volume relationships could overcome errors associated with the intermediate step of inferring DBH from LiDAR. In this study, 60 *Abies grandis* (grand fir: 6-64 cm DBH) were destructively sampled to assess stem volume across the Intermountain West to develop individual tree height-to-stem volume relationships. Results show DBH ($r^2 > 0.98$) and height ($r^2 > 0.94$) are significantly ($p < 0.001$) related to stem volume via power relationships. LiDAR-derived heights provided a 12% RMSE improvement in accuracy of individual tree volume over LiDAR-regressed DBH estimates. Comparing height-based estimates with an existing regional allometry by mapping stem volume in a grand fir dominated stand yielded a 6.3% difference in total volume. This study demonstrates LiDAR's potential to estimate individual stem volume at forest management scales utilizing height-volume relationships.

Key Words

Vegetation; biomass; forestry; LiDAR; allometry

Introduction

The assessment of forest volume and associated biomass provides important baseline information needed to quantify above ground carbon stocks, especially important as forests are estimated to account for ~80% of terrestrial carbon globally ([Dixon et al., 1994](#)). National forest inventory programs aim to provide consistent and robust information for monitoring and reporting of forest resources ([Kangas and Maltamo, 2006](#)). Pan-nationally, programs such as United Nations Collaborative Program on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (REDD) focus on evaluating the quantities of volume and biomass and their dynamics over large spatial scales ([De Sy et al., 2012](#)). At national levels remote sensing techniques have long been explored for their ability to assess the structure and condition of forest vegetation for biomass quantification and monitoring ([Ruimy et al., 1994](#); [Lim et al., 2003](#); [Smith et al., 2014](#)).

Over the last three decades, light detection and ranging (LiDAR) has emerged as the preeminent remote sensing platform for mapping and characterizing forest structure and successional stage ([Nilsson, 1996](#); [Lefsky et al., 1999](#); [Hudak et al., 2008](#); [Falkowski et al., 2009](#); [Nelson, 2013](#)), carbon and biomass ([Lefsky et al., 2002](#); [Hudak et al., 2012](#); [Tinkham et al., 2012](#)), forest inventory attributes ([Goodwin et al., 2006](#)), and canopy height and closure ([Naesset, 1997](#); [Smith et al., 2009](#)), among others. There has been extensive research evaluating how surface generation algorithms and environmental factors influence the accuracy of LiDAR-derived products ([Baltsavias, 1999](#); [Tinkham et al., 2011, 2013](#)). Many LiDAR applications in forestry to date have relied upon small area-based assessments (plot or grid level) that utilize distributional statistics of the LiDAR point cloud in applying classification and regression approaches to infer stand attributes such as volume or biomass ([Hollaus et al., 2009](#); [Naesset et al., 2013](#); [Zolkos et al., 2013](#)). These approaches can provide adequate spatial detail and

accuracy for mapping and monitoring biomass across large regions or to the extent of entire countries. However, a prevailing challenge with such plot- or area-based assessments is the required model calibration to relate the point cloud derived distributional statistics to volume and biomass informed by species at those locations. Furthermore, studies have indicated that estimates of forest volume and biomass over large areas could have improved accuracies when implementing approaches that integrate estimates from individual trees rather than a sole reliance on plot-level assessments (Popescu et al., 2003; Yu et al., 2010; Zhao et al., 2012).

Even as early as the 1940's and 1950's researchers were attempting to use photogrammetry to measure individual tree parameters and achieving standard errors of 0.6 m for both crown diameter and tree height estimates (Nash, 1949; Nyyssönen, 1955). As LiDAR pulse densities and data processing and analysis capabilities have advanced, new applications which required the identification and characterization of individual trees have been increasingly explored. This highly detailed, local, measurement uses LiDAR to directly measure attributes such as the location, crown size, and height of individual trees (Hyypä and Inkinen, 1999; Persson et al., 2002; Falkowski et al., 2006). While these methods breakdown in dense uneven-age stands, they begin to approach the level of accuracy needed to inform operational forest management for timber harvesting. These individual tree measurements have been shown to provide improved accuracy in assessing tree height and volume when compared to plot-based analysis (Yu et al., 2010). Additionally, early comparisons show that using individual tree segmentation techniques to estimate stand level tree volume can achieve greater precision than conventional field inventories (Hyypä and Inkinen, 1999). Most studies utilizing individual tree locations also derive additional tree parameters such as diameter-at-breast-height (DBH) and basal area through regression of tree height metrics, this is typically done so that traditional DBH-based allometric relationships of timber volume and biomass can be utilized (Edson and Wing, 2011; Zhao et al., 2012; Bi et al., 2013; Kankäre et al., 2013). Studies following this approach have found issues with error propagation through the change of equations utilized to regress height to DBH (often through a quadratic relationship) and then estimates of either volume or biomass from DBH (often through a power law) (Zhao et al., 2012; Bi et al., 2013). Several studies have reported DBH RMSE of 11-15% (Vauhkonen et al., 2010) and individual stem volume RMSE of 27-35% RMSE when utilizing regressions of height to DBH (Heurich, 2008). Indirect object-based approaches often utilize machine learning algorithms, such as support vector regression, to relate point cloud distributional metrics to tree attributes (i.e. DBH and stem volume). Generally, these methodologies have achieved similar stem volume estimation accuracies (RMSE 30-35%; Dalponte et al., 2011) to those from regression of height to DBH. More recently, skeleton measurement methodologies have shown promise for improving the accuracy of extracting individual tree DBH values, achieving DBH RMSE of 7-12% (Bucksch et al., 2014). Most object-based (i.e. tree), instead of area-based assessments (i.e. plot or grid), draw upon the direct measurements that LiDAR can provide, rather than modeling of the LiDAR point cloud. However, such object-based approaches face challenges with tree segmentation and species identification accuracy and require the assumption that the object represents an individual tree and not a group of trees. Honing the accuracy of individual tree volume estimates would advance the use of LiDAR in small scale harvest operations, where operational decisions must balance accuracy with data collection costs, reconciling quality, ease of use, processing requirements, and costs (see Avery and Burkhart, 2001).

A prevailing challenge with operationalizing LiDAR for harvest quality forest inventory assessments is the propagation of errors needed to parameterize allometric equations that require

DBH as an input to estimate volume (Ter-Mikaelian and Korzukhin, 1997; Jenkins et al., 2003; Chave et al., 2005), where DBH is most commonly inferred from height measures. However, in North America this is further complicated as many of the available allometric relationships exhibit limited statistical inference as they are commonly derived from a low number of sample trees and a limited range of DBHs (Ter-Mikaelian and Korzukhin, 1997). These DBH based allometry approaches are rooted in the history of forestry, since for centuries DBH was the easiest tree-level measurements to collect (Avery and Burkhart, 2001). However, studies have found that inclusion of individual crown attributes in stem volume predictions from best linear unbiased predictors served to increase accuracy as much as including height (Maltamo et al., 2012).

Alternatively, estimates of stem and stand volume and biomass utilizing different metrics of height have been explored as a way of more directly estimating volume and biomass from remote sensing platforms (Brolly et al., 2012). The connection between plant biomass and height is well documented and results from the relationship between plant maximum height and physiological scaling principals of plant height and capillary diameter (West et al., 1999; Koch et al., 2004). This relationship between plant height and mass has been shown to be roughly constant in one sided competition scenarios, where neighboring trees do not affect growth of dominate trees (Kikuzawa, 1999). Vauhkonen et al. (2010) took advantage of this relationship by developing predictive equations of stand volume by comparing regressions of individual and plot-level tree height to field inventoried plot-level estimates of stem volume finding 12% RMSE of predicted volume for both approaches.

Given the proven ability of LiDAR to accurately measure the height of individual overstory trees (Hyypä and Inkinen, 1999; Maltamo et al., 2004; Falkowski et al., 2006), a logical step is the development of height-based equations to predict tree volume that are not dependent on DBH (Smith et al., 2008; Smith et al., 2014a). Once such height-based tree-level equations are developed, integration up to plot and stand scales should enable volume estimates with reduced errors that would be achievable whether regressing via an intermediate DBH relationship or from spatially modeling canopy height to volume (Smith et al., 2014b). Examples of such height-based allometry have recently been explored for *Pinus palustris* along the Gulf Coast Plain (Gonzalez-Benecke et al., 2014), where results showed varying levels of accuracy ($r^2 = 0.70 - 0.91$) through incorporating ancillary variables such as crown area, site index, and trees per hectare. While the analysis showed potential for estimating stem volume from height, the prediction efficacy broke down when re-applied to the broader ecological range of the species (Gonzalez-Benecke et al., 2014). To further test such relations this study evaluated the following objectives, 1) develop height-based allometric relationships for estimation of second-growth dominant and codominant grand fir stem volume; 2) evaluate the impact of regional differences on the height-based allometric relationship; 3) compare the height-based allometry prediction efficacy with traditional DBH-based methods; and 4) compare height-based stem volume estimates at stand scales with growth and yield modeling estimates.

Methods

Study Area

This study was conducted within the Intermountain West, United States of America (USA), which ranges from eastern Washington to western Montana and from southern Canada south to central Idaho (Figure 1). Sample trees were selected from second-growth mixed conifer forest

stands distributed across a topographically complex landscape, containing a diverse range of habitat types (Cooper et al., 1991). The forests vary in composition of *Abies grandis*, *Pseudotsuga menziesii*, *Pinus ponderosa*, and *Thuja plicata* as moisture availability and soil type changes throughout the study region. Grand fir (*Abies grandis*) was chosen for this case study due to its prolific extent within the forests of the Intermountain West. The field validation site and a portion of the dissected tree samples were located within the University of Idaho Experimental Forest (UIEF) on Moscow Mountain. Other sample trees were selected from the broader range of grand fir within the Intermountain West to include samples from Douglas-fir, grand fir, western red cedar, and western hemlock habitat series, these samples cover a range of DBH from 7-64 cm and heights from 4-30 m corresponding to stem volumes of 0.008-3.640 m³. Further, the trees were selected from a range of local forest structures that varied from 170-650 trees per hectare and 14-83 m² of basal area per hectare, corresponding to stand density indices ranging from 18-640.

Data Collection

A total of sixty sample trees were dissected by two independent experienced measurement groups following similar tree selection and measurement procedures during June and July 2012. Sample trees were located throughout the Intermountain West region to span the common DBH range of second-growth grand fir. All trees were geolocated, with the trees subsequently used for LiDAR analysis located to an accuracy of +/- 1.5 m using a Trimble GeoXT global positioning system (GPS). Prior to felling, outside-bark diameter was recorded at breast height by tape, and total height by a laser hypsometer.

University of Idaho Experimental Forest (UIEF)

The UIEF site ranges in elevation from 770 m to 1,516 m and is actively managed for timber, research, and education purposes. Only dominant and co-dominant trees free of visual defect indicators and with no apparent impacts of past competition were considered for sampling. The twenty-four trees from the UIEF were felled at a 0.61 m stump height to eliminate any butt-swell influence on the bottom log's volume. Bole diameter measurements were collected every 1.83 m along the length of the tree using a Haglof caliper (± 0.1 cm). All logs were defined as 3.66 m long, with diameters recorded at the beginning, midpoint, and end of each log, except the leader which had its length adjusted to correspond with a diameter of 1 cm at the apical meristem. Stump length and diameters were similarly measured at the ground level, midpoint, and felling height of the stump (0.61 m). Diameter inside bark was calculated by subtracting bark thickness (measured using a bark thickness gauge) from diameter outside bark. Tree heights were determined by summing the length of all log segments within each tree. Total stem volume was then determined by summing the log volumes calculated using Newton's formula (Equation 1; Avery and Burkhart, 2001).

$$\text{section cubic volume} = \text{LOGV} = \frac{B+4B_{1/2}+b}{6} \times L \quad [\text{Equation 1}]$$

$$\text{total stem volume} = \sum_i^N \text{LOGV} \quad [\text{Equation 2}]$$

Where, B, B_{1/2}, and b represent the cross-sectional area inside bark at the large, mid-point, and small-end of the log, respectively. To calculate total stem volume (Equation 2), N represents the number of log sections in each tree.

Inland Northwest Growth & Yield Cooperative (INGY)

Thirty-six trees were also selected and dissected by INGY from the broader ecological range that grand fir inhabits within the Intermountain West. Sample trees were selected if they appeared free from past physical damage (i.e. absence of broken tops, forking, harvesting damage, etc.). After felling, total tree height was measured by tape, and paired height and outside-bark diameter measurements were recorded at crown-base, at 1 m intervals within the live crown, and at the 5 cm top (diameter measurements taken by Haglof caliper, ± 0.1 cm). In addition, three discs were cut from each tree, either at systematic intervals (from a random start) or at 4.88 m spacing to preserve the stem's commercial potential. Each disc provided two inside-bark diameter measurements and two bark thickness measurements.

Inside bark cubic volume of the stem was then estimated using the measured height-diameter pairs and the stem-profile method described by Flewelling and Ernst (1996). This methodology calibrates regional stem profile curves to pass through the series of height-diameter pairs taken on an individual tree, and then obtains inside- and outside-bark cubic volumes based on measured bark thickness using numerical integration techniques. The number and arrangement of height-diameter pairs varied by tree according to tree height and crown length, but on average there was one height-diameter pair taken per 1.4 m of stem length.

LiDAR Data

LiDAR data within the UIEF study area were collected in 2009, two growing seasons prior to the destructive sampling, with an average of approximately 12 points m^{-2} . The collection was performed with a Leica ALS 50 operated at 2,000 m above ground level, the system was parameterized to detect up to 4 returns per pulse and to have a maximum scan angle of $\pm 14^\circ$. Additional details regarding the LiDAR processing and development of a 1 m resolution LiDAR digital terrain model and canopy height model can be found in [Hudak et al. \(2012\)](#). Based on the GPS positions of the twenty-four UIEF trees, estimates of tree heights were manually extracted from the LiDAR canopy height model. The canopy height model was also used within the stand validation site (next section).

Stand Testing Data

In order to evaluate the operational inventory potential of a height-based volume allometric equation, a 0.9 hectare stem mapped testing stand was inventoried in August 2012. The testing site was located within the University of Idaho Experimental Forest in an adjacent watershed to where most of the UIEF destructively sampled trees were located. All trees greater than 10 cm DBH within the plot were inventoried by taping their location within an X, Y grid established with a Trimble GeoXT and had their DBH, maximum height, crown competition factor, and species recorded. The site is typical of mid-rotation second-growth forests throughout the region, in this case comprised of 770 trees per hectare, with heights ranging from 10-30 m, with grand fir representing 63% of trees in the stand. For all grand fir ($n = 290$) that were determined to be intermediate, co-dominant, or dominant in their crown competition factor (i.e. receiving at least some direct sun-light), the individual tree X, Y locations within the stem map were utilized to extract and assign the local maximum height value from the LiDAR canopy height model. The local maximum was assumed to represent the location of a single grand fir stem within a 3 by 3 m area. To back-cast tree DBHs so that they would be concurrent with the 2009 LiDAR acquisition, a subsample of thirty diameter growth increments was collected from the grand fir trees across the range of diameters and crown competition factors. These back-casted tree DBH

values were then used to derive individual tree stem volume estimates using the Flewelling Profile Model of the Forest Vegetation Simulator (FVS) – Inland Empire Variant. The Flewelling Profile Model uses measurements of both DBH and height to estimate grand fir total stem volume, the equation is based on methods presented in Flewelling and Raynes (1993). The FVS-derived estimates of total stem volume were calculated from both field and LiDAR-derived measures of DBH and height. From the 0.9 hectare validation stand stem map, LiDAR extracted heights, back casted DBH values, and estimates of stem volume were derived for all grand fir trees using the height-based and FVS allometrics. A kernel density function was then applied to produce spatial maps of grand fir stem volume from both the height-based and FVS approaches for spatial comparison.

Analysis

Linear, logarithmic, power, and exponential function regressions were separately produced for both DBH and height (H) and evaluated against total stem volume (SV), using the curve estimation package in SPSS 21 (IBM, New York). These relationships were assessed across all sample trees in the Intermountain West Region (IMWR) as well as within the separate collection groups (UIEF and INGY). With significant differences in the collection group coefficients tested at a 95% confidence level. Additionally, forward stepwise linear regression was utilized to add ancillary stand variables to the base DBH and H equations to assess their impact on the relationships predictive strength. However, none of the tested variables, including local structural metrics (i.e. trees per hectare and basal area per hectare), site productivity metrics (i.e. habitat type), and local competition metrics (i.e. stand density index and relative density) produced a significant relationship when added to the base equations. Further analysis was conducted to produce a relationship relating H and DBH for analyzing the effect of propagated error. This analysis followed the same steps as those conducted for assessing stem volume. Function fit was defined as the model with the highest level of variation explained (r^2) and lowest root mean square error (RMSE). All regressions were tested at the 95% confidence level, with outliers assessed using Cook's Distance. The two outliers in Figures 2 and 3 (shown by x's) were > 140 years old that did not meet the study constraint of second-growth stems and therefore were removed from subsequent analyses. Removing these trees does narrow the studies scope to not include trees exhibiting old growth physiologic structure.

Results & Discussion

Regressions following a power function provided the best fit (r^2) of the models tested for both DBH and H to predict stem volume and will be the only model form reported and discussed (Tables 1 and Figure 2). Since no significance was found through the addition of parameters describing a trees local growing condition these results are not shown. The model parameters did not show a significant difference when comparing either of the data subsets with the entire IMWR (Table 1). While the RMSE of predicting stem volume from height is increased by 0.156 m^3 compared to the RMSE of the DBH predictions (Table 2), the overall relationships show similar prediction strength (Table 1). Comparison of the destructive sample volume with the allometry predicted volume showed strong correlations ($R > 0.95$), but revealed that the height-based predictions tended to slightly underestimate larger trees (Figure 3) while the DBH-based predictions show a constant bias throughout the range of tree sizes. Such prediction strength demonstrates the potential for height-based allometry estimation of stem volume of second growth grand fir in the IMWR.

Comparison of LiDAR and laser rangefinder measurements of tree total height with dissected measures of total height yielded equally high levels of correlation ($R > 0.98$) and small levels of bias (RMSE < 1.9 m; Figure 4A). In general, the LiDAR height measures were more consistent than the rangefinder height measures except for in two shorter sample trees where adjacent taller trees obstructed the LiDAR measurements giving them high positive errors. Overall, the LiDAR height measurement errors are comparable with measurement errors obtained using traditional equipment to measure tree heights in the field (e.g., laser rangefinder, clinometers, relaskops), which commonly produce errors of $\pm 8\%$ (Williams et al., 1994). The potential to directly utilize LiDAR-derived maximum tree heights is apparent as the LiDAR community has consistently demonstrated that LiDAR measurements of individual tree heights have a small ($< 6\%$) negative bias (e.g., Clark et al., 2004; Anderson et al., 2006; Falkowski et al., 2006) and an absolute error level typically < 1 m.

Evaluating functions to predict DBH from height showed that a power relationship provided the strongest relationship and that there were no differences when analyzed in the data subsets (Figure 4B), resulting in a statistically significant relationship predicting DBH from height across the region ($r^2 = 0.89$, SE = 0.194 cm, $\alpha = 0.05$). This relationship is stronger than most reported in the literature, with past studies demonstrating DBH to height relationships having $r^2 = \sim 0.7$ when considering the ecological range of a species (Zhao et al., 2012; Bi et al., 2013). Propagating uncertainty by parameterizing the DBH-based stem volume relationship with DBH values from LiDAR-derived heights resulted in an approximate 12% increase in RMSE compared to height-based stem volume estimates from the LiDAR-derived heights (Figure 5A). This increased error is attributed to the propagation of errors from the LiDAR measured heights through the height to DBH relationship that is required in parameterizing DBH-based allometrics from LiDAR data.

The allometry equations using DBH and height were also compared against those commonly used in the Inland Empire variant of FVS (Figure 5B). When FVS is parameterized using the field measured DBH and total height reasonable estimates of stem volume were achieved with a RMSE of 0.999 m^3 . However, when parameterized using the LiDAR measured total height and regressed DBH for the UIEF sample trees, there is nearly a 50% reduction in RMSE. The errors seen in FVS's volume predictions from the field measures is largely attributed to FVS's use of a stem profile model, which require other measures of form class (i.e. upper stem diameter) to reach its optimum accuracy. Most of these form class measures are time consuming or impractical to measure either remotely or in the field.

In this study the processing steps required to operationalize the individual tree height-based allometry have been isolated so that the potential of using LiDAR heights could be directly tested. If these additional steps had not been isolated, operationalizing individual tree allometry within a LiDAR inventory would require several processing steps. This processing would first require the delineation of individual trees from the LiDAR point cloud. A number of techniques for detection and delineation of individual trees have been developed, including variations in local maxima, adaptive binarization, region-growing, edge detection, and valley-following. A synthesis comparing multiple segmentation techniques found that dominant and codominant trees could be extracted with 85-100% accuracy depending on tree height and stem density (Kaartinen et al., 2012). While this study found relatively low (30-40%) accuracy at extracting suppressed trees, within our study region suppressed trees provide only a minor contribution to merchantable volume of a stand. Secondly, the approach would require the accurate extraction of individual tree parameters such as height. Most studies report height accuracies of < 0.5 m and an

under prediction bias of ~5% (Persson et al., 2002; Clark et al., 2004; Anderson et al., 2006). Tinkham et al. (2012) found that 0.5 m RMSE of tree heights result in a 1-3% under estimation of timber volume per hectare, with taller forest stand exhibiting smaller estimation errors. Finally, it would be necessary to determine tree species or at least a functional form class for each individual. Species classification accuracies as high as 96% have been achieved using a combination of variables from LiDAR and high resolution (Holmgren et al., 2008). While each of these steps has potential to contribute to the overall accuracy of individual tree LiDAR stem volume estimates, significant advances have been made to improve processing accuracies over the last decade.

Comparing estimates of grand fir stem volume per hectare by parameterizing FVS with tree field measures and using the height-based allometry with LiDAR measured tree heights within the 0.9 ha testing site, there is a 6.3% difference in total estimated stem volume per hectare (Figure 6). Although there are differences when comparing individual tree volume estimates, these differences are modest when looking at the estimates aggregated at practical management scales. This agreement between the traditional inventory allometry approach and the LiDAR-populated height-based allometry approach lends support to the idea of operational LiDAR forest inventories.

Conclusions

This study demonstrates that height-based allometric relationships can be developed across a species ecological range with sufficient accuracy ($r^2 = 0.938$, $RMSE = 0.524 \text{ m}^3$) to be considered for forest management decision making. We see a slight increase in RMSE when comparing the accuracy of our height-based approach with the DBH-based approach derived from the same dataset. However, when compared with a regional standard field-based approach parameterized by regressing DBH from LiDAR measured heights, similar RMSE values were found. When applying the LiDAR-aware allometric equation at an operational forest management scale, there was a 6.3% difference between it and the regional standard estimates.

In summary, direct prediction of stem volume from height prevents propagation of errors by removing the need for the regression of DBH from height, with several examples in the topic area literature (Edson and Wing, 2011; Zhao et al., 2012; Bi et al., 2013). Furthermore, LiDAR-derived predictions of stem volume from height closely resemble those produced using height measurements from a laser rangefinder. This case study shows the potential of height-based allometry to infer stem volume directly for individual trees at spatial scales relevant to forest management. While this study shows promise for direct LiDAR estimates of stem volume, this relationship was only tested for second growth forests. In less intensively managed forests, additional measures of forest structure may be needed to overcome the variation in tree height that different site productivities and growth competition histories can lead to. To fully realize the operational potential of such allometric relationships in forest inventory, additional validation of other species or functional growth form group relationships will be needed (Kimsey et al., 2011). In expanding studies to other species it may be necessary to incorporate other LiDAR-aware metrics (e.g., crown widths, crown heights, crown competition, trees per hectare, etc.) into predictive regression equations.

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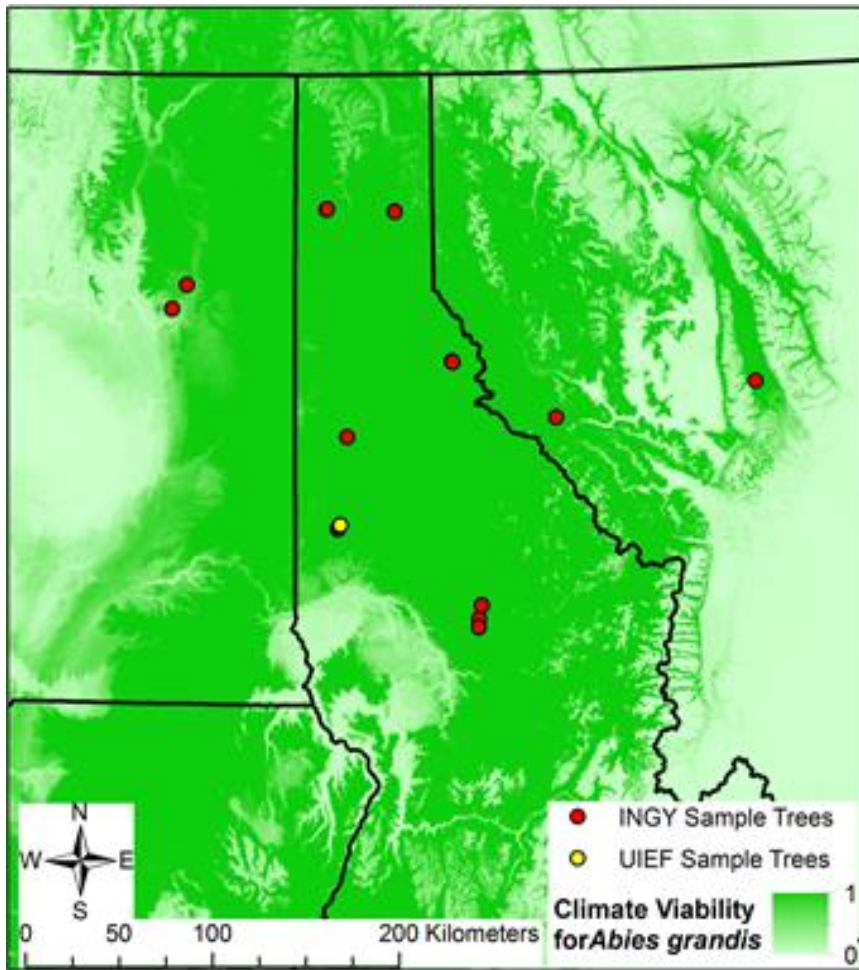


Figure 1. Map of IMWR study area showing location of sample trees across the climate space occupied by *Abies grandis* as modeled by Crookston et al. (2010).

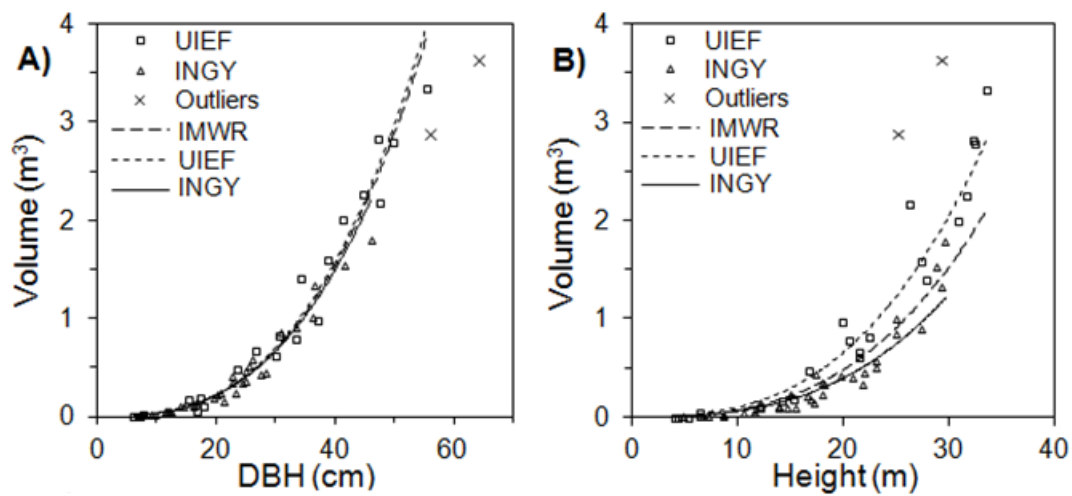


Figure 2. Plotted allometric relationships of A) DBH or B) Height predicting *Abies grandis* stem volume, with lines of best fit passing through the sample subsets.

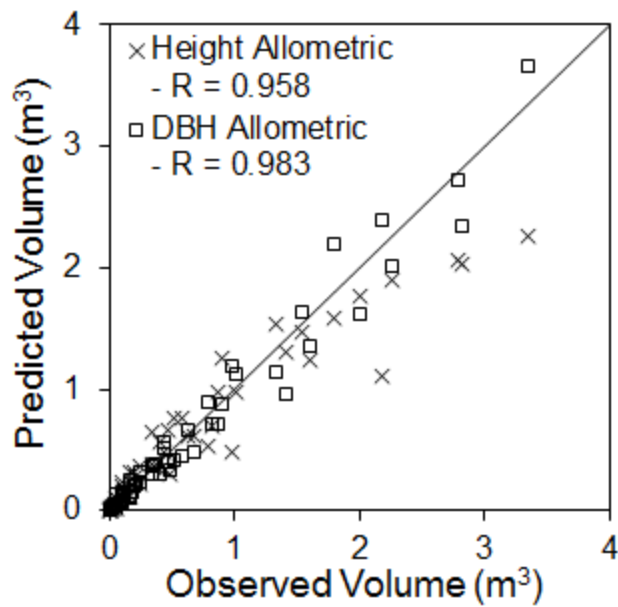


Figure 3. Correlation between observed destructive sample tree stem volume and the height and DBH-based allometric predicted stem volume.

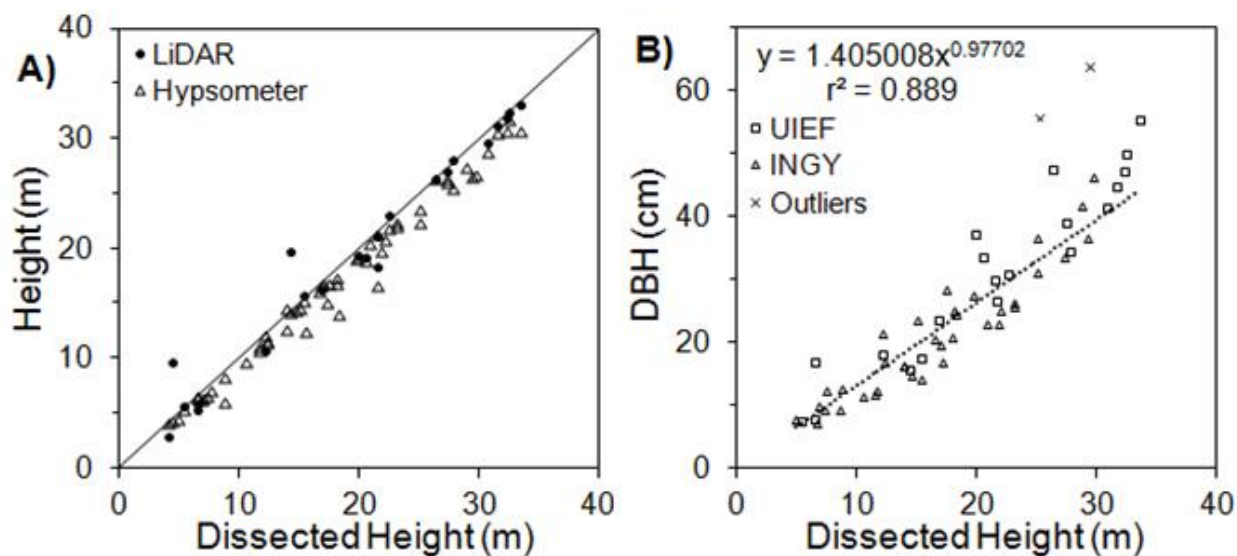


Figure 4. A) Comparison of LiDAR ($n = 22$, $R = 0.98$, $RMSE = 1.87$ m, $bias = -4.1\%$) and hypsometer ($n = 58$, $R = 0.99$, $RMSE = 1.54$ m, $bias = +6\%$) estimates of maximum tree heights to field-dissected measures, with a 1:1 reference line. B) Dissected height to DBH relationship across IMWR sample trees ($n = 58$), with the relationship being significant at the 95% confidence level.

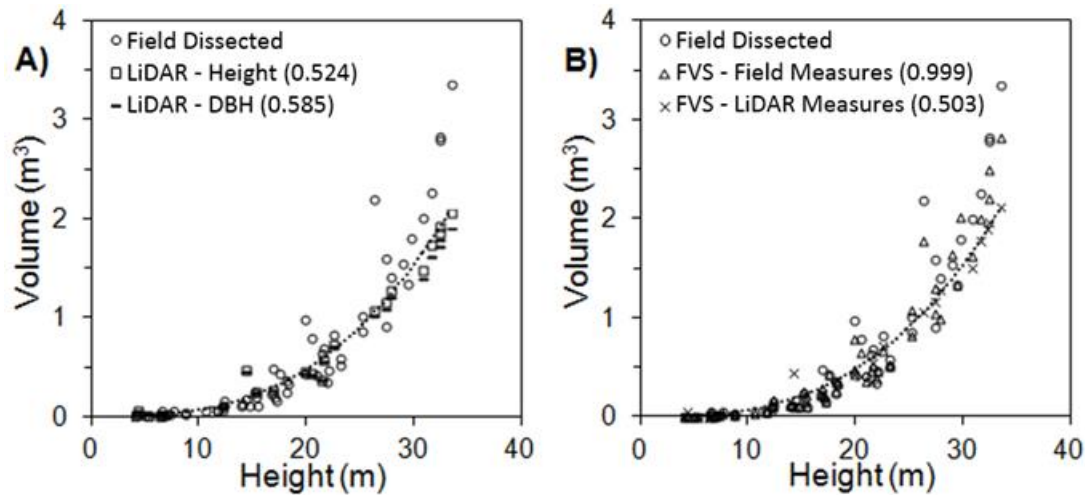


Figure 5. Comparison of field dissected stem volume against (A) height allometrics using LiDAR extracted heights ($n = 22$), DBH-based allometrics using DBH regressed from the LiDAR heights ($n = 22$), (B) Forest Vegetation Simulator – Inland Empire Variant estimates derived from both field ($n = 58$) and LiDAR measures of height and DBH ($n = 22$). The line of best fit passes through all of the field dissected volume and height ($n = 58$). The value in parentheses for each data set is the RMSE (m^3).

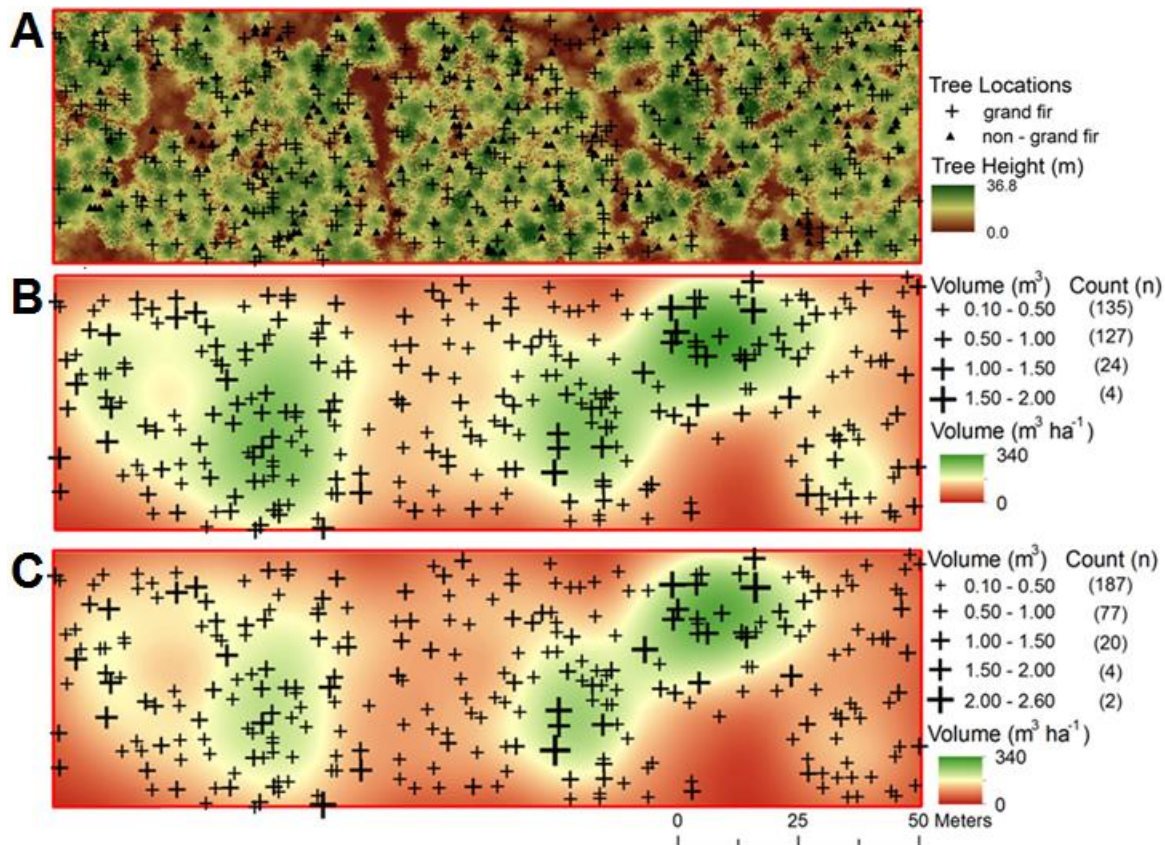


Figure 6. Map of grand fir volume, with (Top) tree locations overlaid on a LiDAR canopy height model. The lower two panels show local volume per hectare kernel density estimates that have been stretched to the same scale for comparison, for (Middle) height-based LiDAR allometric estimates of grand fir volume ($19.9 - 332.1 m^3 ha^{-1}$), and (Bottom) FVS estimates of grand fir volume ($14.5 - 307.8 m^3 ha^{-1}$). While the two approaches produce slightly different distributions of individual tree volumes, there is $< 20 m^3 ha^{-1}$ difference when the volume is aggregated over the area.

Strata	Sample Sets	n =	Equation ($m^3 = aX^b$)		F	r ²	RMSE (m ³)
			a	b			
Height	IMWR	58	0.00008809	2.870470	866.6	0.938	0.323
	UIEF	22	0.00014900	2.800610	758.8	0.973	0.501
	INGY	36	0.00006776	2.892935	611.4	0.946	0.323
DBH	IMWR	58	0.00004487	2.830644	2529.6	0.978	0.157
	UIEF	22	0.00004801	2.818190	893.5	0.977	0.213
	INGY	36	0.00004452	2.827491	1421.5	0.976	0.109

Table 1. Power relationships for total stem volume (SV) from DBH or maximum tree height for the different sample combinations. All relationships are significant at the 95% confidence level.