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Research Article

Geospatial Technologies

An Accuracy Assessment of Field and Airborne Laser Scanning–Derived Individual Tree Inventories using Felled Tree Measurements and Log Scaling Data in a Mixed Conifer Forest

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Abstract

On-the-ground sample-based forest inventory methods have been the standard practice for more than a century, however, remote sensing technologies such as airborne laser scanning (ALS) are providing wall-to-wall inventories based on individual tree measurements. In this study, we assess the accuracy of individual tree height, diameter, and volume derived from field-cruising measurements and three ALS data-derived methods in a 1.1 ha stand using direct measurements acquired on felled trees and log-scale volume measurements. Results show that although height derived from indirect conventional field measurements and ALS were statistically equivalent to felled tree height measurements, ALS measured heights had lower root mean square error (RMSE) and bias. Individual tree diameters modeled using a height-to-diameter-at-breast-height model derived from local forest inventory data and the software ForestView had moderate RMSE (8.3–8.5 cm) and bias (-3.0 – -0.3 cm). The ALS-based methods underdetected trees but accounted for 78%–91% of the field reference harvested merchantable volume and 71%–99% of the merchantable volume scaled at the mill. The results also illustrate challenges of using mill-scaled volume estimates as validation data and highlight the need for more research in this area. Overall, the results provide key insights to forest managers on accuracies associated with conventional field-derived and ALS-derived individual tree inventories.

Study Implications: Forest inventory data provide critical information for operational decisions and forest product supply chain planning. Traditionally, forest inventories have used field sampling of stand conditions, which is time-intensive and cost-prohibitive to conduct at large spatial scales. Remote sensing technologies such as airborne laser scanning (ALS) provide wall-to-wall inventories based on individual tree measurements. This study advances our understanding of the accuracy of conventional field-derived and ALS-derived individual tree inventories by evaluating these inventories with felled tree and log scaling data. The results provide key insights to forest managers on errors associated with conventional field and ALS-derived individual tree measurements.

Keywords: airborne laser scanning, lidar, forest inventory, stem volume, felled tree, log scaling, validation

Forest inventory is a fundamental component of forest management and the forest products supply chain or the flow of wood products from the forest to the end user. Inventory data provides critical information for long-term forest planning, operational decisions, harvest scheduling, investment, and forest product supply chain planning (Maltamo et al. 2021; Tinkham et al. 2018). For more than a century, forest inventories have relied on field sampling of forest stand conditions (Frayer and Furnival 2000; Maltamo et al. 2021), which are time-intensive, accuracy-limited (Luoma et al. 2017) and cost-prohibitive to collect wall-to-wall (i.e., spatially complete) (Durrieu et al. 2015; Vauhkonen et al. 2014a). With advances in remote sensing, forest inventories have shifted toward incorporating technologies such as airborne scanning light detection and ranging (LiDAR), also referred to as airborne laser scanning (ALS), as it can gather wall-to-wall, three-dimensional forest structural data. These technologies can provide wall-to-wall data at a lower cost per unit area than conventional field sampling, especially when applied over large spatial scales or cost-shared (Hudak et al. 2020; White et al. 2016).

Wall-to-wall forest inventories using ALS data are derived either through area-based or individual tree detection (ITD) approaches (Holopainen et al. 2014; Vauhkonen et al. 2014a; White et al. 2016). Area-based methods use gridded summaries of the ALS point cloud (e.g., height percentiles, height stratified

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return densities) and ground-based sampling to model stand-level attributes across the fixed grid (Næsset 2002). Area-based techniques have comparable accuracies to conventional inventory methods for stand-level averages of stem volume, basal area, and height, with root mean square error (RMSE) typically lower than 10% (Persson et al. 2022; White et al. 2016). However, area-based methods have limitations capturing species-specific structural information, which is important for accurate volume estimates and better-informed harvest planning and silvicultural applications (Holopaninen et al. 2014; Keefe et al. 2022; Maltamo et al. 2021; Tompalski et al. 2014). In contrast to area-based methods, ALS-based ITD forest inventories rely on the identification and segmentation of individual trees from ALS point clouds or canopy height models and in some cases can provide near-census-level tree identification. Because ITD provides individual tree geolocation and attribute information, it has significant potential to improve growth and yield projections (Jeronimo et al. 2018; Tinkham et al. 2016), monitor tree-scale growth and mortality (Duncanson and Dubayah 2018), and optimize harvesting and planning (Keefe et al. 2022; Vauhkonen et al. 2014b). Studies have shown that ITD-derived stand level attributes such as mean height, mean diameter at breast height (DBH) and total stem volume are comparable to those derived through area-based analyses (RMSE within ~2%), however, accuracy can vary depending on the pulse density of the ALS data (Frank et al. 2020; Peuhkurinen et al. 2011; Yu et al. 2010). For example, several studies have reported large total stand volume errors (RMSE = ~29%) when ITD methods are applied to low pulse density ALS data (<3 ppm) (Soininen et al. 2022; Vastaranta et al. 2011).

Among the various measurements acquired during a conventional forest inventory, tree height and DBH are two fundamental attributes necessary for forest management and planning because of their correlation with tree competition, volume of wood, and ultimately, forest value (Tinkham et al. 2016; White et al. 2014). Conventional variable-radius-plot sampling and continual forest inventory monitoring approaches vary widely in specifications for the completeness of height and DBH measurements of on-plot trees, often for efficiency purposes (Deo et al. 2016; Scott 1990). Height for any unmeasured tree is often modeled using allometric relationships between DBH and height (Qiu et al. 2021; Wykoff et al. 1982), and there is a long history of allometric relationship development using DBH to model height and other tree attributes for numerous species and size classes (Curtis 1967; Gonzalez-Benecke et al. 2014; Meyer 1940; Qiu et al. 2021). The ALS data, by comparison, can provide highly accurate height measurements but does not directly measure DBH. Thus, research efforts have shifted toward developing allometric relationships that use tree height and other tree attributes, such as crown diameter and tree density, to model DBH, taper, and stem volume (Corrao et al. 2022; Heurich 2008; Popescu 2007; Salas et al. 2010; Tinkham et al. 2016). Modeled DBH derived from ALS data metrics has reported RMSE ranging from ~3.8 to 5.9 cm (Heurich 2008; Popescu 2007; Tinkham et al. 2016). Alternatively, dense point clouds derived from uncrewed aerial systems (UAS) LiDAR and structure from motion (SfM) imagery have been used to directly extract DBH from stem returns with lower RMSE (~0.8–4.8 cm) (Kukkonen et al. 2022; Swayze et al. 2021). Others have used UAS point cloud metrics to model DBH with high accuracy (RMSE = 1.9–2.5 cm) (Sun et al. 2022). Although promising, many present-day UAS are inefficient compared with ALS for large area (i.e., >1,000 ha) data collection (White et al. 2016).

Although the shift from sample-based field inventories to ALS-derived wall-to-wall inventories is promising, the accuracy and errors of measured and modeled individual tree attributes are not well characterized (Lisiewicz et al. 2022; Lara-Gómez et al. 2023). Studies have shown that accurate height measurements are critical for accurate estimates of stem volume and have a greater influence on stem volume error than the choice of generic or species-specific allometric equations (Tompalski et al. 2014). Field measured height has been reported as a reliable way to evaluate ALS-derived individual tree height accuracy (Heurich 2008; Popescu and Wynne 2004; Sparks and Smith 2022; Wang et al. 2019). Field measured height typically relies on indirect measurements from clinometers and/or laser hypsometers that use trigonometric principles to calculate tree height using measurements of angles to the tree base and treetop, along with the horizontal distance to the tree stem. It is widely accepted that these methods generally underestimate the maximum tree height due to treetop occlusion by branches and other trees, especially under dense canopy cover and steep slope conditions, leading to studies questioning whether field measured height is of sufficient accuracy to quantify errors in ALS-derived tree height (Hyyppä et al. 2004; Jurjević et al. 2020; Wang et al. 2019). Conversely, research using direct measurements of height, typically through felled tree measurements, has found ALS-derived heights exhibit less error (RMSE = 0.36–0.41 m) and bias compared with indirect field-measured heights (RMSE = 0.58–1.0 m) (Corrao et al. 2022; Ganz et al. 2019). However, the accuracy of tree heights from ALS can depend on several factors, such as pulse density, scanner type, and processing methods, as other studies have found that field-derived indirect height measurements were more accurate than height measurements derived from low pulse density ALS data (<7 ppm) (Andersen et al. 2006; Soininen et al. 2022; Tinkham et al. 2016). Given the time and cost constraints associated with conducting direct measurement experiments, relatively few studies have undertaken the effort to cut down mature trees, yet information from direct measurement studies remains a critical research need for understanding error associated with conventional and ALS-derived forest inventories. These experiments are also useful for validating novel height derivation methods and new sensor systems that become available such as from UAS.

Postharvest measurements, such as scaled volume, provide an additional independent data source to validate preharvest volume estimates, although few studies have used such datasets. Some studies have used log scale data collected at the processing mill to validate field and ALS-derived stand volume estimates and have found that ALS-derived volume has close agreement with scaled volume (estimates within 10%) (White et al. 2014; Woods et al. 2011). Others have used harvester-derived volume to assess field and ALS-derived estimates and found volume estimates were within ~4%–34% (Holopainen et al. 2010; Korhonen et al. 2008; Persson et al. 2022; Peuhkurinen et al. 2007). Regardless of the method, there are several challenges associated with validation using postharvest volume measurements. Total standing tree volume is often greater than harvester-derived volume due to bucking criteria for standardized log lengths and sizes resulting from small-end-diameter limits, trim allowances (which can be ≥15 cm per log), and desired product types to be milled by processing facilities (Adebayo et al. 2007; Hartsough et al. 1997). Additionally, depending on physical tree defects, such as double tops, crooks, sweep, and/or breakage, a harvester may cut out other portions of a tree bole, further reducing the volume delivered to and scaled at the mill. Furthermore, some log scaling rules systematically underestimate wood volume as they treat segments as nontapering cylinders (Spelter 2004), which can lead to large volume differences between estimated and scaled volume (Fonseca 2005). Regardless of these challenges, comparisons between field-measured, modeled, and scaled volumes provide useful information that is understood by a range of forest research, inventory, and management personnel.

In this study, the overall objective was to assess the ability of conventional field inventory and three ALS-based methods to accurately characterize individual tree height, DBH, and volume in a mixed conifer stand in north-central Idaho, USA. The three ALS-based methods included two “open source” methods that used a common allometric modeling approach and one commercial “gray box” method that used the ForestView software. To address the overall objective we (1) assessed the accuracy of conventional cruise indirect-height measurements and ALS-derived height measurements with direct-height measurements taken after the trees were felled, (2) assessed the accuracy of individual tree diameter derived from local and regional height-to-DBH models and diameter derived from ForestView with direct DBH measurements acquired in the field, and (3) compared modeled gross harvested wood volume calculated from conventional cruise data and ALS-derived height and DBH measurements to the gross volume of harvested logs scaled at the processing mill.

Materials and Methods

Study Area and Experimental Design

This study was conducted within the University of Idaho Experimental Forest (UIEF), located in the Palouse Range of north-central Idaho, USA (~ N 46.82° W 116.80°). The study area focuses on a 1.1 ha mixed conifer stand (figure 1). The study stand was composed of mature trees with an average DBH (±SE) of 38.5 ± 0.9 cm and average height (±SE) of 23.2 ± 0.3 m. Species included *Pseudotsuga menziesii* (Mirb.) Franco var. *glauca* (Beissn.) Franco (Douglas-fir) (72% of live stems), with smaller proportions of *Pinus ponderosa* Dougl. ex Laws. (ponderosa pine) (16% of live stems), *Pinus contorta* Douglas (lodgepole pine) (9% of live stems), *Thuja plicata* Donn ex D. Don (western redcedar) (1% of live stems), *Larix occidentalis* Nutt. (western larch) (1% of live stems), *Abies grandis* (Douglas ex D. Don) Lindl. (grand fir) (0.5% of live stems), and *Picea engelmannii* Parry ex Engelm. (Engelmann spruce) (0.5% of live stems). The local climate is characterized by cool wet winters and warm dry summers. Over the 1991–2020 period, mean summer (June–August) temperature was 17.2°C, mean summer precipitation was 81 mm, and annual precipitation was 622 mm (NOAA 2022).

The stand was thinned in June 2022. Figure 1 shows the ALS-derived canopy height models prethinning (2020) and postthinning (2022). The prethinning tree density was 293.7 trees ha^{-1} and basal area was 37.9 m^2 ha^{-1}. The thinning treatment reduced the tree density to 146.1 trees ha^{-1} and basal area to 21.9 m^2 ha^{-1}.

Field Validation Datasets

A stem-mapped cruise of the trees within the stand was conducted prior to thinning. The irregular shape of the cruised area within the stand (figure 1 “Cruise area”) resulted from active harvesting within the stand prior to the initiation of this research and thus, the boundaries were constrained to the remaining nonharvested area. During the cruise, the location of each tree within the study area was acquired with submeter precision using a JAVAD Triumph-2, which has a reported horizontal accuracy of 0.01 m (JAVAD EMS, Silicon Valley, CA). Unique identification numbers were painted on each tree and each tree was additionally marked with a

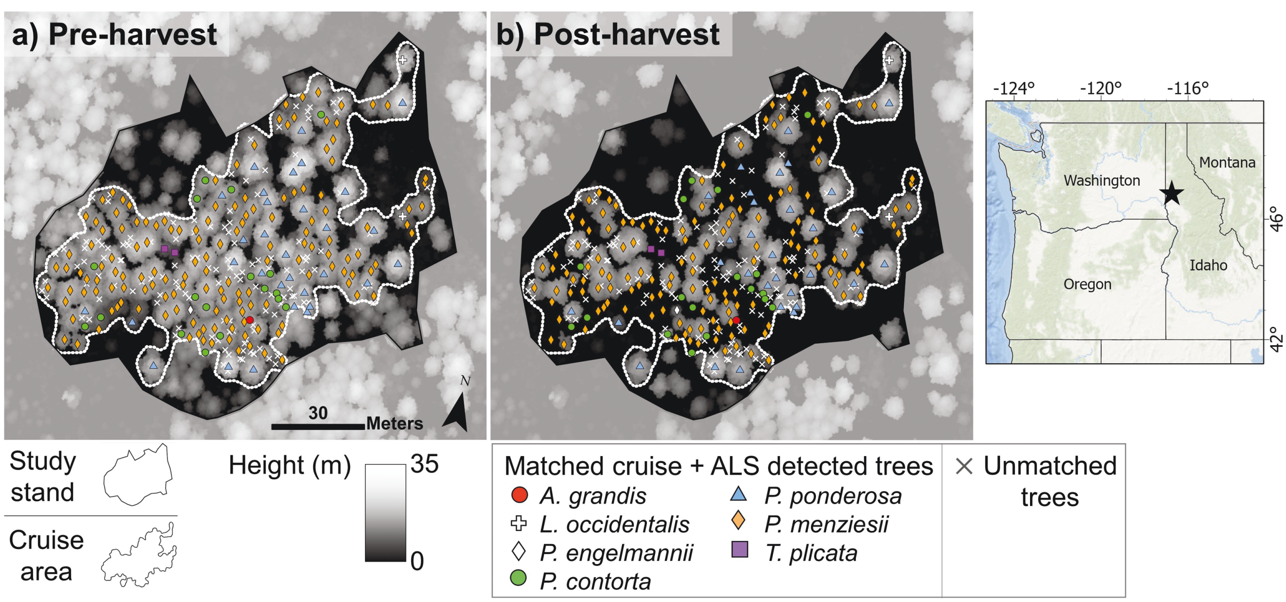

Figure 1 Study location and ALS-derived canopy height models for the study stand and surrounding area (masked area) preharvest (a) and postharvest (b). In (a) and (b), lighter shades indicate greater height and darker shades indicate lower height. Detected and matched individual trees are symbolized by field-classified species and are overlaid on all panes. Unmatched field-geolocated trees are displayed as “×” symbols.

metal tag below stump height. All trees >1.5 m in height were measured for DBH using a logger's tape and for crown base height and total height using a Vertex Laser Geo 360 laser hypsometer (Haglof, Sweden) following standard methods. Height at which the stem diameter is 80% of DBH was also measured for each tree using a Spiegel relaskop (SILVANUS, Kirchdorf, Austria) and was used to inform stem taper. Live or dead status, species and crown position (i.e., dominant, codominant, intermediate, and suppressed) adapted from (Kraft 1884) were also assessed. In total, 339 individual trees were geolocated and measured.

During the thinning treatment, all trees were felled by hand and remained near their respective stump for measurement. The total height for all cruised and felled trees ($N = 191$) was remeasured with a logger's tape from the stump to the end of each leader.

ALS Data and Individual Tree Detection and Measurement

The ALS data were acquired across the study area in September 2020 using a RIEGL VQ-1560II sensor (RIEGL, Horn, Austria) mounted on a fixed-wing aircraft with a gyro-stabilized mount. The sensor has a 58° field-of-view and the aircraft varied the elevation above ground level between 1600 and 1900 m to achieve a 55% flight-line overlap. The average pulse density was twenty pulses per square meter and the average per-pulse return rate was four. The supplier conducted several preprocessing routines, including laser intensity normalization and return classification into bare earth, vegetation, water, buildings, and noise.

Individual tree detection was conducted on the ALS dataset using the ForestView ITD software (Corrao et al. 2022). ForestView ITD was selected as it exhibits comparable detection accuracies (60%–75% of dominant and codominant trees) with other commonly used ITD approaches in mixed conifer forest (Sparks et al. 2022). As described below, following detection of each individual tree, we compared three different approaches to infer DBH and volume. Although the ForestView ITD method is described elsewhere (Corrao et al. 2022; Sparks and Smith 2021), a brief description follows. The ForestView ITD software was developed by Northwest Management Incorporated (NMI, Moscow, Idaho) and provides individual tree location, height, DBH, stem volume, live or dead status and estimates of species. The approach relies on classified ALS point cloud data and derivative datasets including high resolution (0.3 m spatial resolution) canopy height models (CHM). Peaks in the CHM are assumed to be treetops and are detected using CHM and point cloud-based ITD methods, similar to valley following, watershed segmentation, and local max filtering (Popescu and Wynne 2004). Height percentiles, stratified point densities, and crown shape derived from the point cloud for each detected tree are used to refine initial tree detections and derive other tree attribute information (Corrao et al. 2022). Individual tree DBH is modeled using multivariate regression that includes these point cloud metrics in combination with tree dominance, crown radius, live crown height, predicted species, and allometric relationships derived from field-collected verification data (Corrao et al. 2022). The reference data used to train the ForestView model included individual tree GPS locations, heights, species, DBH, live crown heights, and crown widths at various locations across the University of Idaho Experimental Forest. No data from the study stand were used in the training process. Once trained, the final DBH model was applied to the detected trees within the study site. All trees measured in the field were manually matched to ForestView-detected trees using their respective submeter location and height data, a high-resolution CHM (0.3 m spatial resolution), and additional notes taken by the field personnel. In total, 203 of the 339 (60%) cruised trees were successfully matched with ForestView-detected trees and 99 of these trees were felled during the study.

To account for the temporal difference between the ALS data collection (September 2020) and the felled tree data (June 2022), annual height change between September 2020 and June 2022 was calculated by differencing the 2020 ALS scan and an ALS scan acquired in July 2022 for each nonharvested tree in the study site and dividing by the number of growth seasons. Mean annual height increments, aggregated by species, were applied to the 2020 tree heights. These "growth-adjusted" height values were used to calculate three DBH estimates for each tree, two DBH estimates using open-source allometric modeling methods, documented in the following analyses, and one DBH estimate using the ForestView software.

Height-to-DBH Models Developed Using Local and Regional Data

Forest inventory data collected at the local and regional scale was used to derive species-agnostic local and regional height-to-DBH models. The local model used data from an existing dataset of sixty-seven 0.053 ha plots acquired in 2020 across the UIEF (Sparks and Smith 2021; Sparks et al. 2022). As allometric relationships have been shown to vary along competition gradients (Hulshof et al. 2015; Qiu et al. 2021) we only used data from plots that had a basal area per hectare within ±10 m^2 ha^{-1} of our study stand. In total, 747 individual trees were used to develop the local height-to-DBH model.

The regional height-to-DBH model used data from the USDA Forest Service Inventory and Analysis (FIA) program. The FIA program conducts a systematic forest inventory across the entire United States using field-based observations and measurements from permanent plots that are remeasured every 5–10 years (Bechtold and Patterson 2005). We acquired data from conifer-dominated plots in Idaho counties encompassing similar ecoregions to our study area. Specifically, plots within Environmental Protection Agency level IV ecoregions "Northern Idaho Hills and Low Relief Mountains," "Palouse Hills," "Grassy Potlatch Ridges," and "Dissected Loess Uplands" were used (McGrath et al. 2002). Similar to the local model parameterization, we only used data from FIA plots that had a basal area per hectare within ±10 m^2 ha^{-1} of our study area. In total, 1,811 individual trees were used to develop the regional height-to-DBH model.

Relationships between height and DBH for both the local and regional scales were assessed using regression modeling, where DBH was the response variable and height was the predictor variable. Linear, logarithmic, and power-law function regression models were evaluated separately for each dataset. The best fit model was determined by the lowest Akaike Information Criterion (AIC) value (Akaike 1974). The best fit model using local and regional data was applied to the growth-adjusted ALS-derived heights to model DBH for each tree in the study area.

Height and DBH Accuracy Assessment

Several statistical tests were used to evaluate the similarity of cruised and ALS-derived individual tree height and DBH to felled tree height and DBH. A Kolmogorov-Smirnov test was used to assess whether cruised and ALS-derived height distributions were statistically similar to the felled tree height distribution. This test further assessed the similarity of modeled and ALS-derived DBH distributions to the cruised DBH distribution. The Kolmogorov-Smirnov test identifies differences in the cumulative distribution function of two data distributions. The test statistic (D) is the maximum difference between the cumulative distribution functions, where D values close to 0 indicate significant overlap in the data distributions and values close to one indicate little to no overlap in the data distributions. For this test, the null hypothesis is that the test dataset distribution follows a reference dataset distribution, and the alternate hypothesis is that the distributions are not similar. The null hypothesis is rejected if $P < .05$. This test is particularly useful for quantifying the similarity of the shape of two distributions. For example, two distributions with the same mean but different shape will produce large D values.

The accuracy of cruised and ALS-derived individual tree height and DBH was assessed using regression-based equivalence tests (Robinson et al. 2005). For these tests, the null hypothesis is that the regression slope and intercept between paired sets of data are significantly different, and the alternate hypothesis is that they are not significantly different. A linear regression model is fit using the paired datasets and an upper and a lower one-sided 95% confidence interval for both the intercept and slope is computed using the standard error regression outputs. The null hypothesis of dissimilarity is rejected if the joint one-sided 95% confidence intervals are entirely contained within a user-defined region of equivalence (e.g., ±X%). Intercept equality implies the means of two datasets are not significantly different and slope equality implies that the regression slope is not significantly different than one. Many similar studies (Corrao et al. 2022; Falkowski et al. 2008; Robinson et al. 2005; Sparks and Smith 2021; Sparks et al. 2022) have used an arbitrarily selected region of equality (±25%) for the intercept and slope. Here, we follow the Robinson et al. (2005) suggestion of reporting the minimum region of equivalence that would still result in the rejection of the null hypothesis of dissimilarity. Equivalence was assessed separately between cruised tree height and felled tree height and ALS-derived tree height and felled tree height. Similarly, equivalence between modeled DBH (local and regional models) and cruised DBH and ALS-derived growth-adjusted DBH and cruised DBH were also assessed. The average RMSE (1) and mean bias (2) were calculated for all modeled and ALS-derived height and DBH as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{x} - x_i)^2}{n}} \tag{1}$$

$$Mean\ bias = \frac{\sum_{i=1}^{n} (\hat{x} - x_i)}{n} \tag{2}$$

where $\hat{x}$ are the predicted values, x_i are the observed values, and n is the number of observations. All statistical analyses were conducted in R (R Core Team 2023), and we used the "equivalence" R package (Robinson 2016) to conduct the regression-based equivalence tests.

Comparison of Harvested Volume

We calculated gross harvested merchantable and pulp volume for all harvested trees within the cruise area and compared the total volume estimated by the cruise and ALS-derived methods. Specifically, we compared total volume estimates for (1) matched cruise and ALS-detected trees and (2) all trees within the cruise area (i.e., matched and unmatched trees). The cubic volume of each harvested tree was calculated using five sets of height and DBH measurements: (1) felled height and cruised DBH, (2) cruised height and DBH, (3) ALS-derived height and DBH modeled using the local forest inventory dataset, (4) ALS-derived height and DBH modeled using the regional forest inventory dataset, and (5) ForestView-derived height and DBH. For all sets of measurements, we estimated diameter inside bark using the Kozak (2004) taper equation from 0.3 m, assumed to be the stump height, to the treetop in 0.5 m segments. We used regionally derived taper equation parameters (Pancoast 2018; Poudel et al. 2018) and the Smalian formula (3) for calculating the cubic volume (V, m^3) of all segments of each harvested tree:

$$V = \frac{L}{2}(A_1 + A_2) \tag{3}$$

where L is the length of the log (m), A_1 is the area of the small end of the log (m^2), and A_2 is the area of the large end of the log (m^2). The total volume of each tree was calculated as the sum of merchantable volume, or volume of the stem where the diameter was greater than 15.24 cm, and pulp volume, or volume of the stem where the diameter was less than 15.24 cm but greater than 7.62 cm. All harvested individual tree volumes were summed to provide gross harvested merchantable and pulp volume for the cruise area. The volume derived using felled heights and cruised DBH was assumed to be the most accurate and served as the reference volume estimate.

We also compared gross harvested merchantable volume for the entire study stand to scaled merchantable volume conducted at the processing mill. Harvest of the study stand largely occurred on separate days from harvesting of the surrounding stand, so it was possible to assign harvested trees within the study area to the specific truckloads taken to the mill. One exception was a single harvesting day where logs from the study area and the surrounding stand were mixed. Ground personnel estimated that up to two truckloads out of the six for that day originated from the study area. Due to this complexity, we report scaled volume with uncertainty bounds ranging from zero truckloads (0% of harvested volume for that day) to two truckloads (~33% of harvested volume for that day).

All logs on ten out of the twelve log loads originating from the study stand were scaled at the processing mill using the Scribner decimal C log rule. This log rule estimates the number of one-inch-thick boards spaced one-quarter inch apart that can fit inside the circular area of a log's smallest end. Board foot yield of this scaling cylinder can be calculated by summing the widths of each board, dividing by 12, and multiplying by the length of the log. Most logs are tapered and are not perfect cylinders, which means that this method ignores volume outside the scaling cylinder. Other cubic scales provide a more accurate estimate of total usable fiber (e.g., Newton and Smalian cubic volume formulations), however, the Scribner decimal C log rule remains one of the most widely used log scaling rules in the western United States (Saralecos et al. 2014; Spelter 2004). The volume of the two remaining loads was estimated via a weight-to-volume conversion factor. The two weight-scaled loads were taken to the mill on the same day as the other Scribner-scaled loads and had similar species proportions. The mill data provided species, gross and net board feet, and net tons for each log load harvested from the study area. Given that smaller diameter second-growth trees tend to be more tapered and thus have higher volume underestimation (Spelter 2002), gross board feet were converted to cubic volume using log-diameter dependent conversion ratios compiled by the Idaho Board of Scaling Practices (IBSP 2018).

The scaled merchantable volume provided a reference volume range to compare with the ALS-derived volume. Cruise-derived volume estimates were not compared to scaled volume as the entire stand was not cruised (figure 1).

Results

Individual Tree Height Accuracy

Individual tree height distributions and associated cumulative distribution functions for cruised tree height and felled tree height are shown in figure 2a and b. Tree height distributions and associated cumulative distribution functions for ALS-derived growth-adjusted tree height and felled tree height are shown in figure 2c and d. Both cruised and ALS-derived growth-adjusted height means were within 0.5 m of the felled height mean and both distributions exhibited similar distribution shape to the felled tree height distribution (figure 2a and c). The Kolmogorov-Smirnov test statistic D was close to zero for cruised height versus felled height (D = 0.152, P = .169) and for ALS-derived growth-adjusted height versus felled height (D = 0.121, P = .44), indicating significant overlap between the paired distributions. Given the P-values were greater than .05, the null hypothesis that the cruised and ALS-derived height distributions follow the felled height distribution was not rejected.

The regression-based equivalence tests for cruised heights versus felled heights and ALS-derived growth-adjusted heights versus felled heights are shown in figure 3a and b, respectively. The intercept values for the cruised versus felled height and ALS-derived growth-adjusted versus felled height relationships were equivalent at a region of equivalence of ±4% or greater and ±3% or greater, respectively. The slope values for the cruised versus felled height and ALS-derived growth-adjusted versus felled height relationships were equivalent at a region of equivalence of ±14% or greater and ±11% or greater, respectively. The linear relationship between cruised height and felled height had a high r^2 (0.88) and low RMSE (1.52 m) and bias (-0.47 m). Similarly, the linear relationship between ALS-derived growth-adjusted height and felled height had a high r^2 (0.88) and low RMSE (1.48 m) and bias (0.32 m).

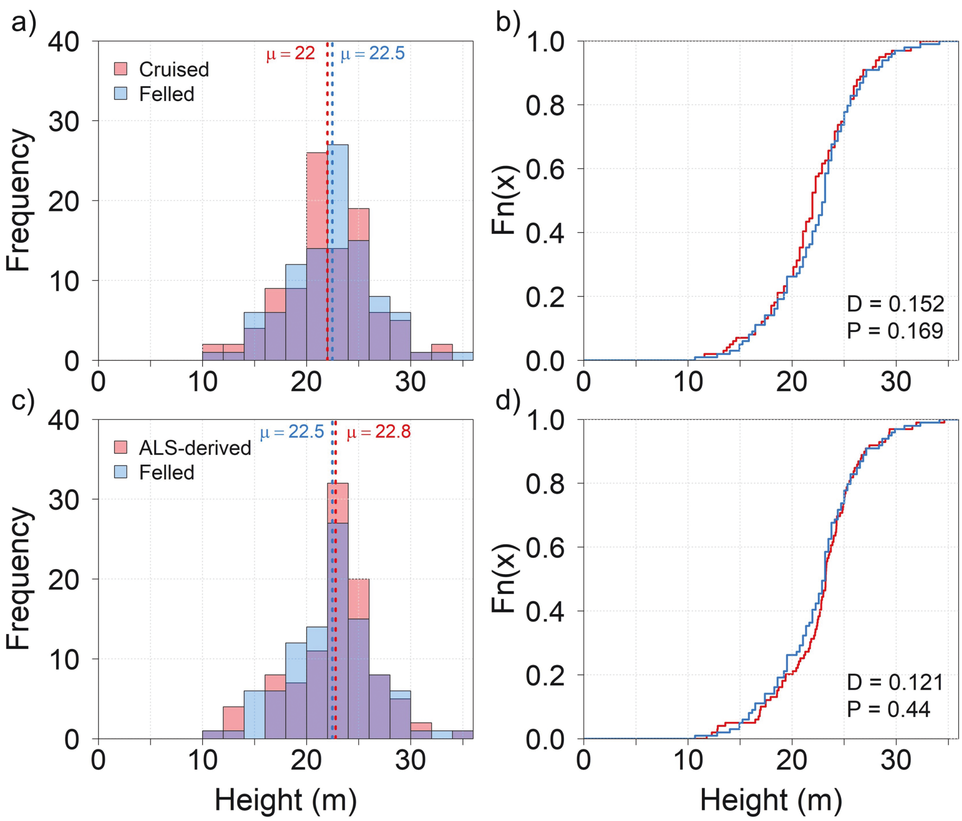

Figure 2 Individual tree height distribution comparison and associated cumulative distribution functions for cruised tree height versus felled tree height (a,b) and ALS-derived growth-adjusted tree height versus felled tree height (c,d). Data for the ninety-nine matched and felled trees are shown. In (a,c), purple coloration indicates where the two distributions overlap and the dashed vertical lines indicate the mean of each distribution. The Kolmogorov-Smirnov test statistic D and associated P-value are reported for each of the paired distributions in (b,d).

Height-to-DBH Models

Figure 4 shows the allometric relationships between height and DBH for the local forest inventory dataset (figure 4a) and the regional forest inventory dataset (figure 4b). The best-fit regression model for both the local and regional datasets used a power-law function (local results: power-law AIC: 350.7, logarithmic AIC: 11278.6, linear AIC: 10889.8; regional results: power-law AIC: 300.2, linear AIC: 12447.5, logarithmic AIC: 12714.5). The relationship between height and DBH for the local dataset had a high r^2 (0.80) and low residual standard error (0.3 cm). The relationship between height and DBH for the regional dataset had a lower r^2 (0.70) and low residual standard error (0.3 cm).

Individual Tree DBH Accuracy

Figure 5 shows individual tree DBH distributions and associated cumulative distribution functions derived from the local and regional height-to-DBH models and ForestView in comparison with the cruised DBH distribution. All models produced unimodal DBH distributions with a peak around 30 cm, whereas the cruised DBH distribution was bimodal with peaks around 25 cm and 40 cm. The Kolmogorov-Smirnov test statistic D was closer to zero than one for all modeled DBH versus cruised DBH tests, indicating significant overlap in the paired distributions. However, the null hypothesis that the modeled DBH distribution follows the cruised DBH distribution was rejected for both the

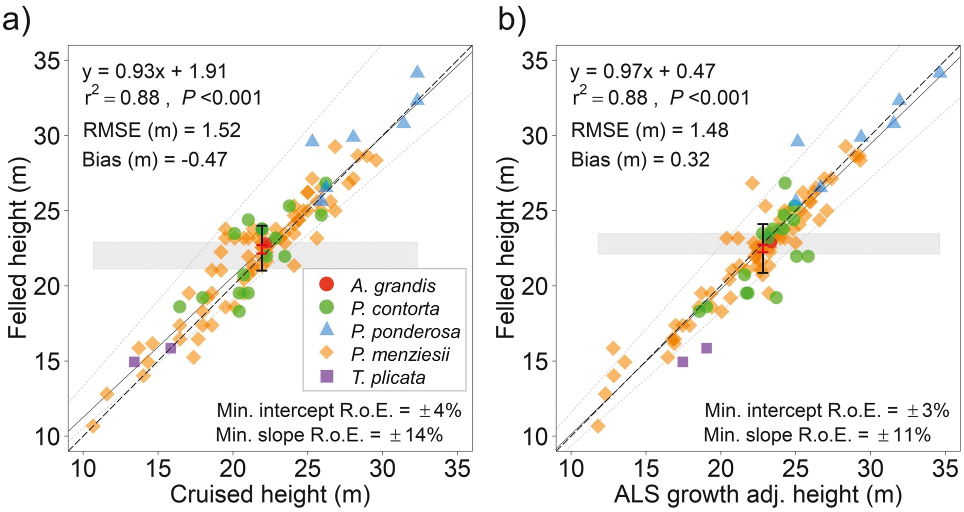

Figure 3 Regression-based equivalence test graphs for cruised height versus felled height (a) and ALS-derived growth-adjusted height versus felled height (b). Data for the ninety-nine matched and felled trees are shown. The minimum region of equivalence (R.o.E.) that would still lead to rejection of null hypothesis of dissimilarity is reported for both the intercept and slope. The grey polygon represents the minimum region of equivalence for the intercept. The cruised and ALS-derived mean heights are equivalent to the mean felled heights when the vertical red bar is completely within the grey polygon. The grey dashed lines represent the minimum region of equivalence for the slope. If the vertical black bar is within the grey dashed lines, then the regression slope is significantly similar to one. The solid black line represents the best-fit linear regression model, and the black dashed line represents the 1:1 line. The coefficient of determination (r^2) and associated *P*-value for the linear regression models are also presented. Individual trees are symbolized by field-classified species and are shown for illustrative purposes.

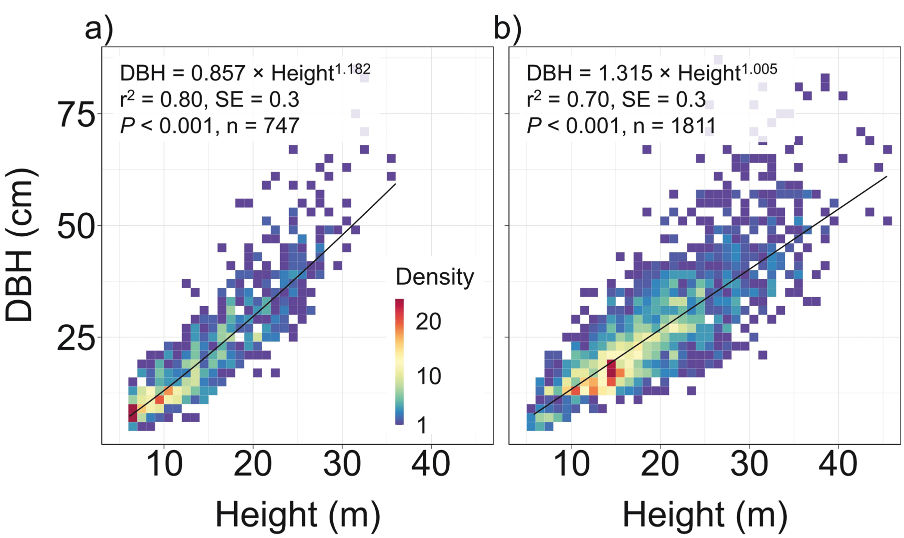

Figure 4 Relationships between height and DBH using the local forest inventory dataset (a) and the regional forest inventory dataset (b). The black line represents the best-fit regression model. The scatterplot point densities, calculated using a ~2 × 2 quantization of the plot axes, are displayed with a rainbow color scale.

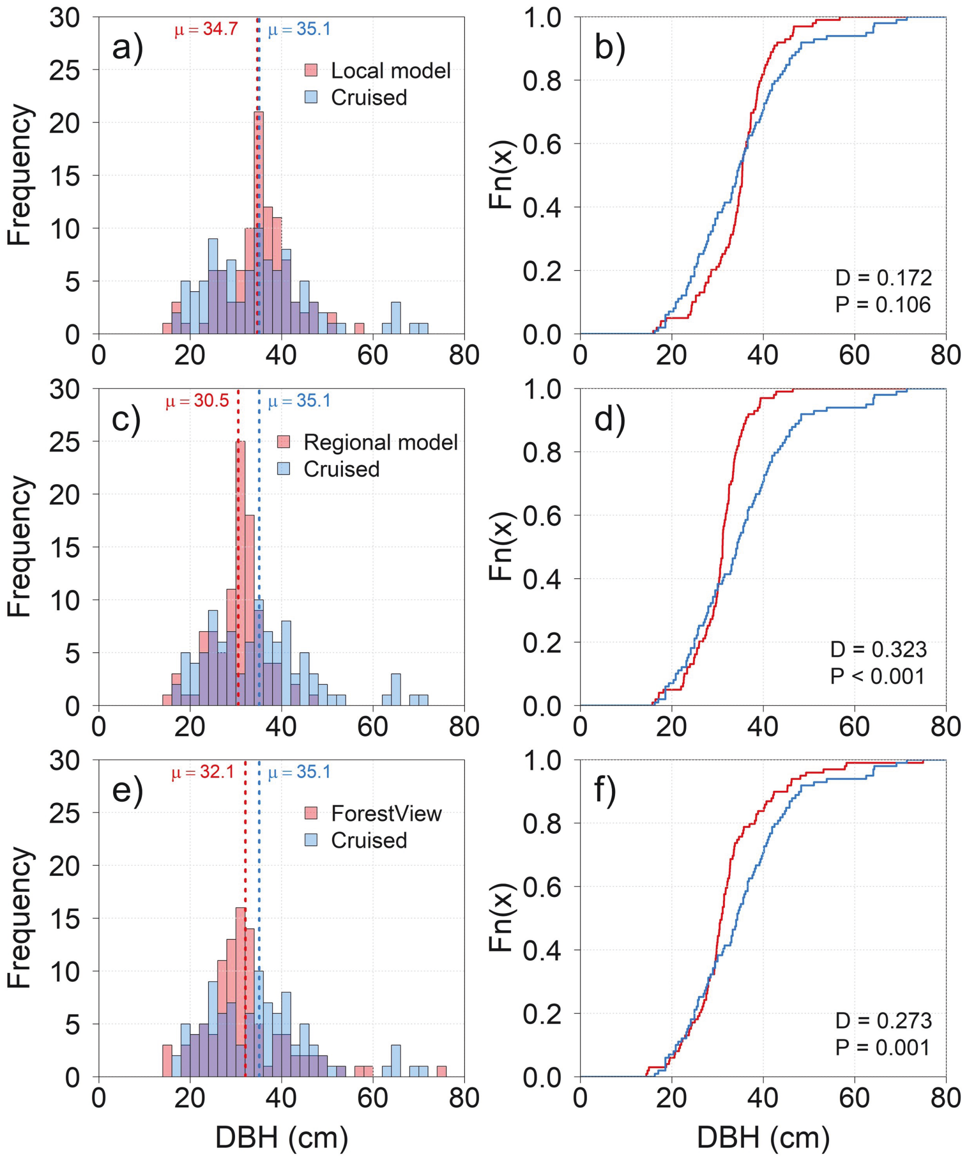

Figure 5 Individual tree DBH distribution comparison and associated cumulative distribution functions for the local model-derived DBH versus cruised DBH (a,b), the regional model-derived DBH versus cruised DBH (c,d) and ForestView-derived DBH versus cruised DBH (e,f). Data for the ninety-nine matched and felled trees are shown. In (a,c,e) purple coloration indicates where the two distributions overlap and the dashed vertical lines indicate the mean of each distribution. The Kolmogorov-Smirnov test statistic D and associated *P*-value are reported for each of the paired distributions in (b,d,f).

regional-modeled DBH ($P < .001$) (figure 5c and d) and ForestView-modeled DBH ($P = .001$) (figure 5e and f). The null hypothesis that the local forest inventory data–modeled DBH distribution follows the cruised DBH distribution was not rejected ($P = .106$).

The DBH modeled using the local dataset exhibited a -0.4 cm bias and RMSE of 8.5 cm compared with the cruised DBH, whereas DBH modeled using the regional dataset exhibited a -4.6 cm bias and RMSE of 10 cm compared with the cruised DBH. The DBH modeled using ForestView exhibited a -3.0 cm bias and RMSE of 8.3 cm compared with cruised DBH. The regression-based equivalence tests for modeled DBH versus cruised DBH are shown in figure 6. The intercept and slope for the local dataset modeled DBH versus cruised DBH relationships were equivalent at a region of equivalence of ±6% or greater and ±33% or greater, respectively (figure 6a). Similarly, the intercept and slope for the ForestView-modeled DBH versus cruised DBH relationships were equivalent at a region of equivalence of ±14% or greater and ±23% or greater, respectively (figure 6c). The intercept and slope for the regional dataset modeled DBH versus cruised DBH relationships were equivalent at a region of equivalence of ±20% or greater and ±75% or greater, respectively (figure 6b).

Comparison of Harvested Volume

The gross harvested merchantable and pulp volume for cruised and felled trees that were matched with ALS-detected trees is shown in figure 7a. Gross harvested merchantable volume calculated using the cruise data (83.4 m^2), local (81.4 m^3) and regional (61.7 m^3) forest inventory datasets and ForestView (72.0 m^3) were 0.7%, 3.1%, 26.5%, and 14.3% lower than the reference volume derived from felled heights and cruised DBH (84.0 m^3), respectively.

The gross harvested merchantable and pulp volume for all trees within the cruise area (matched and unmatched) is

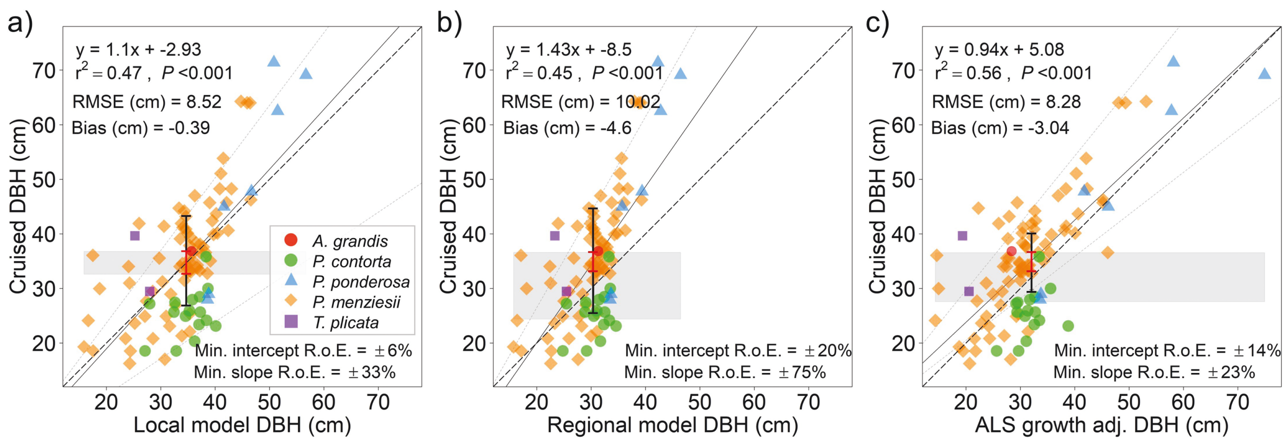

Figure 6 Regression-based equivalence test graphs for local model-derived DBH versus cruised DBH (a), regional model-derived DBH versus cruised DBH (b), and ForestView-derived DBH versus cruised DBH (c). Data for the ninety-nine matched and felled trees are shown. The smallest region of equivalence (R.o.E.) that would still lead to rejection of null hypothesis of dissimilarity is reported for both the intercept and slope. The grey polygon represents the minimum region of equivalence for the intercept. The modeled DBH means are equivalent to the cruised DBH mean when the vertical red bar is completely within the grey polygon. The grey dashed lines represent the minimum region of equivalence for the slope. If the vertical black bar is within the grey dashed lines, then the regression slope is significantly similar to one. The solid black line represents the best-fit linear regression model, and the black dashed line represents the 1:1 line. The coefficient of determination (r^2) and associated *P*-value for the linear regression models are also presented. Individual trees are symbolized by field-classified species and are shown for illustrative purposes.

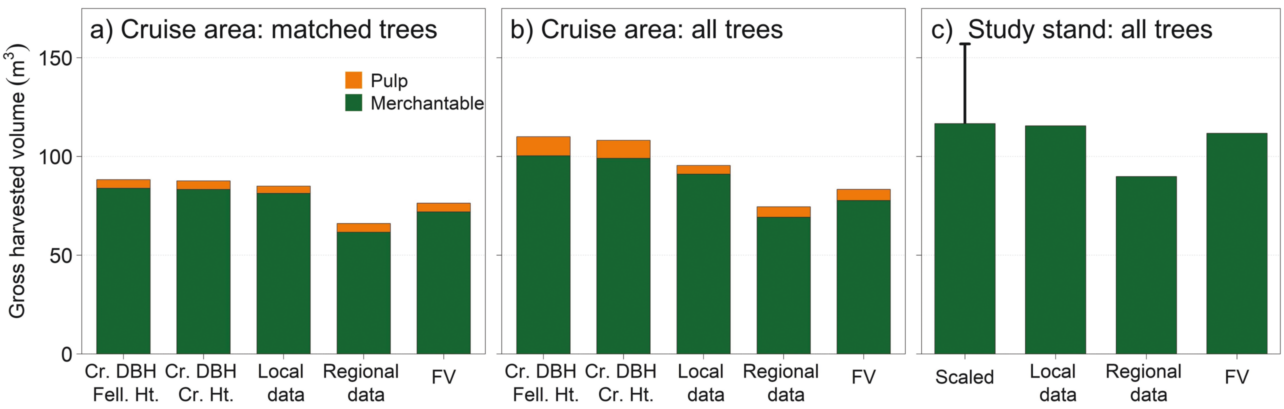

Figure 7 Comparison of gross harvested volume differentiated by pulp and merchantable volume, for (a) matched and felled trees within the cruise area, (b) all trees within the cruise area (matched and unmatched), and (c) all trees within the study stand. Due to the reported uncertainty in log loads, only merchantable volume is shown in (c). "Cr. DBH Fell. Ht." volume was calculated using felled height and cruised DBH measurements; "Cr. DBH Cr. Ht." volume was calculated using cruised height and DBH measurements; "Local data" volume was calculated using ALS-derived height and DBH modeled using the local forest inventory dataset; "Regional data" volume was calculated using ALS-derived height and DBH modeled using the regional forest inventory dataset; and "FV" volume was calculated using ForestView-derived height and DBH. The "Scaled" volume error bar in (c) shows the estimated range of volume due to uncertainty in log loads taken from the study area on one harvesting day.

shown in figure 7b. Gross harvested merchantable volume calculated using the cruise data (99.1 m^3), local (91.1 m^3) and regional (69.3 m^3) forest inventory datasets and ForestView (77.8 m^3) were 1.3%, 9.3%, 30.1%, and 22.5% lower than the reference volume derived from felled heights and cruised DBH (100.4 m^3), respectively.

The gross harvested merchantable volume for all trees within the study stand is shown in figure 7c. Due to uncertainty in truckloads taken from the stand on one harvesting day, scaled gross harvested merchantable volume ranges from 116.7 to 157.0 m^3. Gross harvested merchantable volume calculated using ALS-derived height and DBH modeled using the local (115.6 m^3) and regional (89.9 m^3) forest inventory datasets and ForestView (111.8 m^3) were 1%–26.4%, 23.0%–42.7%, and 4.2%–28.8%, lower than the reference scaled volume, respectively.

Discussion

This study assessed individual tree height and DBH accuracy derived from conventional forest inventory methods and three ALS data-derived methods. We show that although both indirect heights from cruising and ALS-derived height were statistically equivalent to direct height measurements on felled trees at regions of equivalence of ±3% or greater for the intercept and ±11% or greater for the slope, ALS-derived height exhibited lower RMSE and bias. The comparison results also show that DBH modeled using a generic height-to-DBH allometric relationship derived using local field data and DBH modeled using ForestView are statistically equivalent to cruised DBH at regions of equivalence of ±6% or greater for the intercept and ±23% or greater for the slope. On the contrary, DBH modeled using regional field data was statistically equivalent to cruised DBH at regions of equivalence that were much greater (±20% or greater for the intercept and ±75% or greater for the slope). This finding suggests that locally derived height-to-DBH models will likely provide more accurate estimates of individual tree DBH than DBH modeled using regional datasets. When considered with other studies (Heurich 2008; Persson et al. 2002; Popescu and Wynne 2004; Salas et al. 2010; Tinkham et al. 2016), these height-to-DBH results are promising, as they suggest DBH can be modeled with relatively high accuracy for ALS-detected trees. The comparison of estimated gross harvested merchantable volume extends this finding further by showing that the best ALS methods volume estimates accounted for 78%–91% of the field reference harvested volume and 71%–99% of the scaled volume. However, as these results represent a single mixed conifer stand, this analysis should be repeated in other stands/forest types.

Detection of individual trees is a primary driver of ALS-derived individual tree inventory accuracy. Most ITD approaches detect dominant and codominant trees, some intermediate trees, and miss most subcanopy trees. As may be expected, the detection rate is highly dependent on stand density (Eysn et al. 2015; Sparks et al. 2022; Vauhkonen et al. 2012), ALS data density (Duncanson and Dubayah 2018; Marinelli et al. 2019; Soininen et al. 2022; Wang et al. 2016), and tree detection approach. The ITD benchmarking studies have shown that different approaches can detect between 66% and 85% of dominant and codominant trees, whereas subdominant trees are detected at much lower rates (<~31%) (Eysn et al. 2015; Sparks et al. 2022; Vauhkonen et al. 2012; Wang et al. 2016). Underdetection of trees can result in biased mean height and DBH (Vauhkonen et al. 2010) and large stand volume errors (RMSE: ~29%) (Vastaranta et al. 2011). Underdetection of subdominant trees may not present an issue for managers primarily interested in merchantable stand volume and biomass, as dominant trees represent the majority of stand volume and biomass and subdominant trees are associated with lower value pulp products (Lutz et al. 2012; O'Hara 1988; Vastaranta et al. 2011). For example, Persson et al. (2002) showed that although 71% of trees were detected within their study stands, dominant trees represented ~91% of total stem volume. On the other hand, managers concerned with growth and yield projections may need understory regeneration and ingrowth information depending on their silvicultural objectives. Modeling undetected trees, such as using theoretical height distribution functions, may provide a way to supplement automatic ITD approaches and more accurately estimate stand-level parameters (e.g., Maltamo et al. 2004). In this study, we matched trees manually, with an overall detection rate of 60%. Like other studies, we show that despite the underdetection of trees, a majority of the reference merchantable volume (derived from felled heights and cruised DBH) was estimated by the local data–derived ALS method (90.7%), the regional data–derived ALS method (69.0%) and ForestView (77.5%) (figure 7b). The largest error source in volume estimation was the underdetection of trees (omission error), followed by error in DBH and height. For example, when only considering the omission error (i.e., assuming no error in DBH and height) for the most accurate ALS method (local data derived ALS method), merchantable volume error was 16%, whereas only considering DBH error or height error resulted in volume errors of 6% and 2%, respectively. Likewise, when only considering omission error, pulp volume error was 55%, whereas only considering DBH error or height error resulted in volume errors of 15% and 4%, respectively. Vastaranta et al. (2011) also observed larger volume error (29%) when the only error source was omission error (omission error of 39.8%) than when the only error source was DBH or height error (volume error less than 1.2%). Given the large error in volume due to undetected trees observed in this study and others (Vastaranta et al. 2011), more research is warranted to explore approaches that increase the tree detection rate.

This study supports prior work demonstrating that individual tree heights derived from high pulse density ALS (i.e., >20 ppm) exhibit less measurement error than conventional indirect field measurements. Studies using high pulse density ALS have shown that ALS-derived individual tree heights have lower RMSE (0.36 m for *Pseudotsuga menziesii*, 0.41 m for *Pinus taeda*) than heights derived from indirect field measurements (1.02 m for *Pseudotsuga menziesii*, 0.58 m for *Pinus taeda*) (Corrao et al. 2022; Ganz et al. 2019). Similarly, we found that ALS-derived height had lower RMSE (1.48 m) than indirect field measurements (1.52 m) for the conifers assessed in this study. The height RMSE in this study is likely higher than other studies due to error introduced by averaging height change between the ALS acquisitions. Nevertheless, indirect field tree height measurements are known to have greater measurement error due to observer bias, obscuration of tree bases and treetops by other trees, undergrowth, and terrain (Hyyppä et al. 2004; Wang et al. 2019). Thus, high pulse density ALS is likely superior to indirect field measurements in many cases. In contrast, studies using lower pulse density ALS (i.e., <7 ppm) have shown that ALS-derived individual tree heights have slightly higher RMSE (0.73 m for *Pseudotsuga menziesii* and *Pinus ponderosa*, 1.87 m for *Abies grandis*) than heights measured using indirect field methods (0.27 m for *Pseudotsuga menziesii* and *Pinus ponderosa*, 1.54 m for *Abies grandis*) (Andersen et al. 2006; Tinkham et al. 2016). This result agrees with prior studies where low pulse density ALS was shown to underestimate individual tree heights at pulse densities lower than 7 ppm (Yu et al. 2004; Zhao et al. 2018). Thus, indirect field measurements may be more accurate than ALS for measuring height in forests where ALS with ≤~8 ppm is available (Soininen et al. 2022). In all cases, ALS has the advantage of providing wall-to-wall measurements of individual tree height, whereas acquiring wall-to-wall field measured height is logistically and economically infeasible.

Our results show that DBH can be modeled with moderate accuracy from ALS-derived height measurements. Both the DBH modeled using a species-agnostic field measurement–derived height-to-DBH allometric relationship and ForestView-derived DBH were statistically equivalent to field-measured DBH and had moderate RMSE (8.5 cm and 8.3 cm, respectively) and bias (-0.4 cm and -3.0 cm, respectively). Although statistically equivalent, the distribution shape mismatch between modeled DBH (unimodal distribution) and observed DBH (bimodal distribution) (figure 5) suggests that species-specific height-to-DBH models may be preferrable to generic height-to-DBH models. For example, *Pseudotsuga menziesii* and *Pinus ponderosa* diameter tended to be underpredicted (figure 6) and *Pinus contorta* diameter tended to be overpredicted (figure 6), likely due to their different growth forms. Beyond species, modeling DBH using more tree attributes and stand and site predictors would likely produce a more accurate result. Studies that have modeled DBH using both height and crown diameter as predictor variables have achieved lower DBH errors (RMSE: 3.8–5.9 cm) than those in this study (RMSE: 8.28–10 cm) (Heurich 2008; Persson et al. 2002; Popescu 2007; Salas et al. 2010). For example, Popescu (2007) observed an RMSE of 4.9 cm in *Pinus taeda* L.–dominated stands, Persson et al. (2002) observed RMSE of 3.8 in *Picea abies* L. Karst. and *Pinus sylvestris* L. stands, and Heurich (2008) observed RMSE of 4.6–5.9 in *Picea abies* and *Fagus sylvatica* stands. It is likely that incorporating a refined screening process in the local and regional height-to-DBH modeling to select plots with similar site conditions to our study stand would result in more accurate DBH estimates. However, including simple height-to-DBH models in this analysis is useful information in cases where a forest manager has limited ALS-derived data and processing capability (i.e., no available individual crown diameter data). Additionally, like the observed height error, RMSE in this study is likely higher than in other studies due to error introduced by using average diameter growth between the ALS acquisition in 2020 and felled tree measurements in 2022. Tree DBH modeled from UAS LiDAR and SfM data has been shown to have higher accuracy (RMSE: ~0.8–4.8 cm) than DBH modeled from ALS data (Kukkonen et al. 2022; Sun et al. 2022; Swayze et al. 2021), however, data acquisition using ALS is more efficient over large areas (i.e., >1,000 ha) compared with present day UAS (White et al. 2016).

Scaled volume provides a promising independent validation data source; however, as this study illustrates, there are many challenges and uncertainties associated with using this data. First, it should be noted that although we tried to minimize tree detection and matching errors using manual matching methods, the overall detection rate was 60%. This underdetection is likely the primary factor of the ~1%–29% merchantable volume underestimation of the top ALS methods. Second, uncertainty in log loads originating from the study area is a significant source of volume error. Tracking harvested trees is a challenge given that harvesting and log transport logistics sometimes necessitate mixed log loads that incorporate harvested trees from different parts of the stand or multiple stands. Third, as volume of two of the twelve log loads was estimated via a weight-to-volume conversion factor, underestimation or overestimation could occur due to weight-to-volume conversion factor error. Furthermore, the Scribner-scaled loads could be underestimated compared to volume calculated using the Smalian formula, as this rule assumes a quarter-inch kerf allowance. Uncertainty in ALS-estimated DBH and board feet to cubic volume conversion factors could contribute to the volume mismatch. The ALS-based methods tended to underpredict DBH (figure 6), which directly translates into lower individual tree volume estimates than cruised volume estimates (figure 7a). We could not find error estimates associated with board feet to cubic volume conversion factors, which is a research need, considering the widespread use of both board feet and cubic volume in the western United States (Saralecos et al. 2014; Spelter 2002, 2004) and the likely increasing use of scaled volume as ALS-derived forest inventory validation data. Other studies have shown moderate agreement between ALS-derived volume estimates and postharvest volume measures. White et al. (2014) found that volume derived from cover type–adjusted volume tables underestimated weight scale volumes by 19.8% whereas volume derived from ALS area-based analysis had much closer agreement to weight scale volumes (+0.6%) in coniferous boreal forest in Alberta, Canada. Likewise, Woods et al. (2011) reported that mean area–based analysis estimates of stand volume from ALS data were within 10% of scaled volume in a coniferous boreal forest stand in Ontario, Canada. Other studies have shown that individual tree volume derived from ALS measurements was within ~4% of harvester-derived individual tree volume (Peuhkurinen et al. 2007).

A potential limitation of this study was the number of matched individual trees (*N* = 99), representing five conifer species from a single stand. Although this may appear to be a small sample size, it is comparable to the upper end of previous studies using direct measurements on felled trees or high-precision measurements acquired using terrestrial laser scanning (TLS). Although focused on a single stand, the species variability in this study is also greater than most earlier studies that mainly focused on only one or two species. For example, Tinkham et al. (2016) used measurements from 60 felled *Abies grandis* in the intermountain western United States, Sibona et al. (2017) used measurements from 100 felled conifers in the Italian Alps, Ganz et al. (2019) used measurements from 30 felled *Pseudotsuga menziesii* in Germany, and Corrao et al. (2022) used measurements from 139 felled *Pinus taeda* in the southern United States. Likewise, Andersen et al. (2006) compared ALS measurements to TLS measurements for fifty-nine total *Pseudotsuga menziesii* and *Pinus ponderosa* individuals. The primary reason for these small sample sizes is the time and person hours required to acquire felled-tree measurements. It is also often infeasible to fell trees or collect measurements on felled trees due to safety or logistical issues, leading most ITD validation studies to use field-collected indirect heights. However, studies that use direct measurement are critical for validation of remotely sensed measurements, and the relative lack of such studies indicates that more are needed to assess ALS-derived measurement accuracy across diverse species and stand conditions. Equally, these types of field measurements are essential for assessing the accuracy and utility of larger spatial scale projects and commercial applications.

Conclusions

Accurate forest inventories are necessary for forest management and forest products supply chain planning. This study advances our understanding of the accuracy of conventional field and ALS-derived individual tree inventories by evaluating these inventories with felled tree measurements and log scaling data in a coniferous forest stand with diverse species composition and structure. The results show that although ALS-derived and indirect field measurements of height are statistically equivalent to direct height measurements, ALS-derived height had lower RMSE (1.48 m) and bias (0.32 m) for this stand than field measurements (RMSE = 1.52 m, bias = -0.47 m). Our results also highlight the utility and uncertainty of using ALS-derived individual tree height to model DBH. In this stand, although both ForestView-derived DBH and DBH derived from local height-to-DBH models were statistically equivalent to field measured DBH, RMSE was moderate (8.3–8.5 cm). The results show that the largest error source in volume estimation was the underdetection of trees, followed by error in DBH and height. Like prior studies, this study shows that although there was an underdetection of trees (60% detection rate), the best ALS-derived volume estimates accounted for 78%–91% of the reference gross harvested merchantable volume estimated via felled heights and field-measured DBH measurements. The comparison of estimated gross harvested merchantable volume and scaled volume extends these findings by showing that these ALS-based methods accounted for 71%–99% of the scaled gross volume. However, this study also highlights the challenges of using scaled data as validation, including tracking log loads, volume underestimation associated with the log scaling methods, and error associated with board feet to cubic volume conversion factors. More research is warranted on these topics given the likely increasing use of scaled volume as ALS-derived forest inventory validation data. Overall, the results highlight the potential—and uncertainty associated with—using high pulse density (≥20 ppm) ALS to conduct individual tree inventories in mixed-species coniferous forests.

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Conflict of Interest

M.V. Corrao and R. Armstrong are employed by Northwest Management Incorporated.

Data Availability

The data underlying this article were provided by Northwest Management Incorporated and will be shared on request to the corresponding author with permission of Northwest Management Incorporated.

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