remote sensing

Technical Note

Examining the Role of UAV Lidar Data in Improving Tree Volume Calculation Accuracy

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Abstract: Traditional forest inventories are based on field surveys of established sample plots, which involve field measurements of individual trees within a sample plot and the selection of proper allometric equations for tree volume calculation. Thus, accurate field measurements and properly selected allometric equations are two crucial factors for providing high-quality tree volumes. One key problem is the difficulty in accurately acquiring tree height data, resulting in high uncertainty in tree volume calculation when the diameter at breast height (DBH) alone is used. This study examined the uncertainty of tree height measurements using different means and the impact of allometric models on tree volume estimation accuracy. Masson pine and eucalyptus plantations in Fujian Province, China, were selected as examples; their tree heights were measured three ways: using an 18-m telescopic pole, UAV Lidar (unmanned aerial vehicle, light detection and ranging) data, and direct measurement of felled trees, with the latest one as a reference. The DBH-based and DBH–height-based allometric equations corresponding to specific tree species were used for the calculations of tree volumes. The results show that (1) tree volumes calculated from the DBH-based models were lower than those from the DBH–height-based models. On average, tree volumes were underestimated by 0.018 m^3 and 0.117 m^3 for Masson pine and eucalyptus, respectively, while the relative root-mean-squared errors (RMSEr) were 24.04% and 33.90%, respectively, when using the DBH-based model; (2) the tree height extracted from UAV Lidar data was more accurate than that measured using a telescopic pole, because the pole measurement method generally underestimated the tree height, especially when the trees were taller than the length of the pole (18 m in our study); (3) the tree heights measured using different methods greatly impacted the accuracies of tree volumes calculated using the DBH–height model. The telescopic-pole-measured tree heights resulted in a relative error of 9.1–11.8% in tree volume calculations. This research implies that incorporation of UAV Lidar data with DBH field measurements can effectively improve tree volume estimation and could be a new direction for sample plot data collection in the future.

Keywords: field measurement; allometric equation; tree volume; UAV Lidar

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1. Introduction

Forests play important roles in maintaining global carbon cycling and biodiversity. Regular forest inventories at certain time intervals are the main approach to quantifying forest resources and monitoring their dynamics. Generally, forest inventory involves the field measurement of individual trees within preset plots based on sampling theory. The sample plot is a basic unit for providing information on both individual tree levels and forest stand levels [1]. In recent years, remote sensing technology has been widely applied in forest surveys across large areas, and a variety of remotely sensed data including optical, radar, and Lidar with different modeling approaches from simple linear regression to complicated deep learning have been used to estimate forest attributes [2–6]. No matter what remotely sensed data or algorithms are used, sample plot data aggregated from single trees are required for both model development and model validation [7]. By building relationships between remote sensing-derived variables and forest attributes of in situ plots, the continuous distribution of the forest attributes in a study area can be predicted [6,8]. Therefore, accurate measurements of sample plots are crucial for both traditional forest inventories and remote sensing-based modeling approaches.

Forest stock volume is a main element of a forest inventory. The total forest stock volume for a given area is estimated based on the volumes of a large number of representative sample plots, while the forest volume of a sample plot is the sum of the volumes of all individual trees within the plot, expressed as the volume per area unit. The individual-tree volume is calculated using species-specific allometric equations based on tree diameter at breast height (DBH) or the combination of DBH and tree height, which are measured in the field. Thus, the measurement precision of tree parameters and the choice of allometric equations highly affect the data quality of sample plots. Generally, there are two broad categories of allometric equations: single-entry equations with DBH alone as predictor (DBH-based) and double-entry equations with both DBH and tree height as predictors (DBH–height-based).

Current national forest inventories in China uniformly use DBH-based volume tables to calculate tree volumes for easy comparison between consecutive surveys. These DBH-based volume tables are specific to a province or local area and are derived from the standard DBH–height-based volume tables according to the local site conditions and forest growth situations [9,10]. Studies have shown that the accuracy of a stem volume estimated from a DBH–height-based model is generally higher than that from a DBH-based model when only considering the uncertainty caused by the allometric models [11,12]. A comparison of the volume estimates using DBH-based and DBH–height-based models for Masson pine (*Pinus massoniana*) and Chinese fir (*Cunninghamia lanceolata*) indicated that the relative errors were between 40% and 60% at tree level [13]. In addition to the estimation accuracy, the variance in volume estimates using a DBH–height-based model is smaller than that using a DBH-based model, indicating a higher stability of volume estimation [14]. However, when tree height is added into an allometric equation, the uncertainty of volume estimates caused by height measurements is much higher than that caused by DBH alone. There have been reports showing more accurate volume estimates using a DBH-based model than using a DBH–height-based model due to the high uncertainty in height measurements [15]. This is due to the fact that measuring DBH is much easier and more precise than measuring tree height in the field. Therefore, obtaining accurate tree height is crucial when using a DBH–height-based model to calculate tree volume. However, it is not easy to measure the heights of standing trees accurately in forests, especially in mountainous regions.

Common methods to used measure tree heights involve the use of instruments such as telescopic poles, laser altimeters, clinometers, and hypsometers [16], among which the telescopic pole is the easiest to operate just by lifting the top of a pole to the same level as the top of the tree. This method is suitable for small trees because of the limited pole length (18 m in our study). When the tree height is higher than the pole length, the tree height measurement may have large errors. Moreover, it is hard to judge whether the top of a pole is at the same level as the top of a tree in dense forests. Another common method is to use a laser altimeter, which is based on the triangulation relationship between the distances from the altimeter to the tree base and treetop [17]. However, using a laser altimeter is also a challenge in a forest site due to the complex and dense canopy structures, especially in sites with steep slopes in mountainous regions.

Lidar techniques, particularly airborne Lidar, with their powerful capability of capturing accurate 3-dimensional (3D) information of ground features, are proven to be important means for providing accurate vertical forest structures, and are widely used to assist traditional in-situ forest inventories [18,19] or to estimate various forest structure parameters, including tree height [17], canopy height [20], canopy density [20,21], species diversity [22], above-ground biomass [23], and stock volume [6]. Unmanned aerial vehicles (UAVs), as an alternative remote sensing platform, have advantages over manned aircrafts or satellites in real-time applications, such as easy operation and low costs [24]. UAVs equipped with precise GPS fly at remarkably low altitudes, offer very high-spatial resolution optical images or high-density Lidar point clouds, from which different tree attributes are retrieved accurately [25,26]. In particular, UAV Lidar with a high point density can accurately depict the 3-D structure of individual trees and has been regarded as an important data source for extracting tree height in recent years [27,28]. For instance, Dalla Corte et al. [27] analyzed the correlation between direct tree height measurements and Lidar-derived tree heights at the individual tree level, and obtained a correlation coefficient of 0.91 and a relative root mean square error of 7.9%; Cunha Neto et al. [29] examined the impact of Lidar point densities on height extraction accuracies of *Araucaria angustifolia* trees in an urban Atlantic rain forest, and found no significant differences when the point density was greater than 25 point/m^2. Those studies demonstrated the potential of UAV Lidar systems for measuring forest plantations, reducing field workloads, and providing an important tool to assist in decision making for forest management.

The importance of incorporating tree height with DBH for tree volume calculation is recognized, but rarely has research examined the uncertainty between using or not using tree height in the allometric equations for calculating volume. Therefore, this research aimed to (1) improve the understanding of using UAV Lidar in extracting tree height through comparative analysis with tree height measurements using a telescopic pole and direct measurement of felled trees; (2) understand the effects of using accurate tree height measurements on tree volume calculations; (3) understand the necessity of using DBH–height-based allometric equations by comparing them with DBH-based ones in providing high-quality tree volume data.

2. Materials and Methods

2.1. Study Area

Two experimental sites—Yuanling Forest Farm in Yunxiao County and Baisha Forest Farm in Shanghang County, Fujian Province, China (Figure 1)—were selected. This region has a subtropical monsoon climate with an average annual temperature of 19–21 °C and average annual precipitation of 1730 mm. These two sites have undulating terrains with elevations between 34 and 730 m and slopes between 15 and 50 degrees. Eucalyptus is the dominant tree species in the Yuanling Forest Farm, and Masson pine and Chinese fir are the dominant tree species in the Baisha Forest Farm.

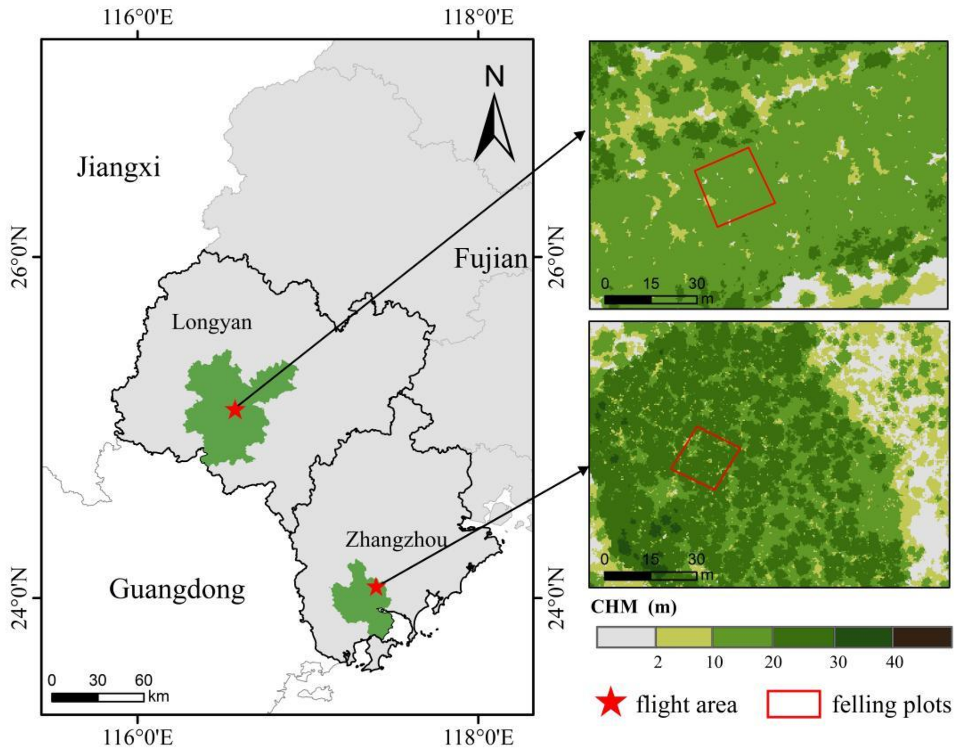

Figure 1. Locations of the experimental sites: Baisha (**upper right**) and Yuanling (**lower right**). CHM represents canopy-height model data generated from UAV Lidar.

2.2. Field Measurements of Individual Trees

Field surveys were conducted in July and August 2021. One eucalyptus plot and one Manson pine plot measuring 20 m × 20 m each were set up. The geographic coordinates of each corner of the plots were precisely located using real-time kinematic (RTK) global positioning system (GPS). Topographic characteristics such as elevation, slope, and aspect were also described. The DBH of each tree within a plot was measured using a diameter tape, while the heights of the selected trees were measured using an 18-m telescopic pole before cutdown. For trees taller than 18 m, the portions above 18 m were estimated visually. The location of each tree was recorded using RTK GPS; the sketch of tree positions relative to one another was drawn in the field, and the precise tree spatial distribution map, based on the RTK records, was created later in the laboratory. After trees were felled, the heights of all felled trees (used as reference data) were measured again using an adequately long tape. Table 1 presents counts of all trees within plots, number of trees measured using the telescopic pole, and numbers of felled trees, as well as the ranges of DBH and height of the felled trees for each species.

Table 1. Plot characteristics of eucalyptus and Masson pine.

Plot	Number of All Trees within the Plot	Number of Trees Measured with the Telescopic Pole	Number of Felled Trees	DBH of Felled Trees (cm)	Height of Felled Trees (m)
Eucalyptus	51	17	50	5.1–25.2	6.5–26.6
Masson pine	37	30	35	13.1–27.6	11.4–22.8

Note: DBH, diameter at breast height.

2.3. Collection of UAV Lidar Data and Extraction of Individual Tree Heights

UAV Lidar data were acquired in July and August 2021. The RT470 multirotor UAV carrying the R1350 Lidar system flew at a height of 150 m over predesignated areas in

Yuanling and Baisha Forest Farms. Point clouds with a density of 40–80 pts/m^2 covering a total area of about 18 km^2 were obtained for these sites (Figure 1). The major process of the UAV Lidar point clouds included filtering, denoising, normalizing, and generating canopy-height model (CHM) data [30]. The data providers classified Lidar point clouds into ground and nonground points by a filtering process. Denoising included removal of low points, air noise, and isolated points. Meanwhile, we manually identified power lines and deleted them from the Lidar data. Based on ground and nonground points, DEMs (digital elevation models) and DSMs (digital surface models) at different pixel sizes (0.3–1.0 m) were generated using inverse-distance-weighted interpolation, and the CHMs were obtained by subtracting DEM from DSM.

In order to extract individual tree heights from Lidar data, one critical step was to generate a single-tree crown image through a proper segmentation approach. Commonly, there are two approaches used for single-tree segmentation based on point clouds and in Lidar-derived CHM [31–34]. The CHM-based method is to identify single trees through a pixel growth algorithm; it is fast and efficient. However, during the process of generating CHM, some information is lost, leading to missing trees beneath the canopy [35]. The segmentation based on Lidar point cloud data adopts a local-maximum method and produces a tree crown based on seed points, avoiding the loss of data. Corresponding to the segmentation methods for individual trees, there are two ways to extract individual tree height: the maximum CHM data within each segment or the maximum point clouds within the same tree crown [36]. Of the various segmentation algorithms, such as marker-controlled watershed, mean-shift clustering, graph-cut segmentation, and the tree-crown boundary-transformation method based on fishing net dragging, the marker-controlled watershed method based on CHM has been widely used in single-tree crown segmentation [37–39]. Thus, we also used it in this research. In addition, different cell sizes were tested, and an optimal resolution of 0.4 m was identified for CHM segmentation. The maximum value of the CHM within a segmented tree crown was taken as the height of that tree. For the understory trees, the crowns of which could not be detected by tree segmentation, treetop positions were determined by visually examining the normalized Lidar point clouds from different views around the tree locations recorded by RTK on the tree distribution map. Once the treetop positions were identified, the tree heights were determined, which were equal to the values of normalized Lidar points at the treetop positions.

2.4. Evaluation of Tree Height Measurement Results

The felled-tree height measurements were used as reference data, and the tree height values obtained using a telescopic pole and UAV Lidar were evaluated through comparative analysis of the assessment factors—Pearson correlation coefficient (r), bias (bias), relative deviation (bias%), root mean square error (RMSE), and relative root mean square error (RMSEr) [16]. For this purpose, the tree heights measured from 17 felled eucalyptus trees and 30 felled Masson pine were used as validation samples because only those trees were measured using all three height-measuring methods.

2.5. Calculation of Tree Volumes for Different Tree Species

The objective of accurately measuring DBH and height is to calculate tree volume using a suitable allometric equation for a specific tree species. In general, the allometric equations can be based on DBH alone or on the combination of DBH and height. Previous research has shown that the DBH–height-based equations produce higher accuracies and more reliable results than the DBH-based ones if the tree height is accurately measured [12,40]. In order to understand the uncertainty caused by using or not using the tree height variable in the allometric equations, this research selected the following two equations to calculate volume for eucalyptus and Masson pine, respectively:

$$V = a \times D^b \tag{1}$$

$$V = a \times D^b \times H^c, \tag{2}$$

where V is the single-tree volume, D and H are DBH in cm and tree height in m; a, b, and c are model parameters for specific tree species as summarized in Table 2.

Table 2. Coefficients of the allometric equations for different tree species.

Tree Specie	Allometric Equation	a	b	c	Reference
Eucalyptus	DBH-based	0.00019854	2.35261		
	DBH–height-based	0.000071748	1.897944	0.839915	[41]
Masson pine	DBH-based	0.00013881	2.48492		
	DBH–height-based	0.000066937	1.941140	0.90485	[42]

Note: DBH, diameter at breast height; a, b, and c are model parameters for specific tree species.

2.6. Impacts of Tree Height on Tree Volume Calculation

In order to examine the impact of tree height on volume calculation, we designed different scenarios, as summarized in Table 3. The individual-tree volumes calculated using the DBH–height-based allometric equations based on the tree heights from the felled trees were used as volume reference data. Bias and RMSE were used to evaluate the accuracy of single-tree volume results based on DBH alone, or tree heights from the telescopic pole and Lidar data.

Table 3. Scenarios of examining the role of the tree height variable in calculation of single-tree volume.

Role of Height	Allometric Equation	Description
Using height or not	DBH-based equation vs. DBH–height-based equation by using reference height	Understanding the role of tree height variable in improving calculation accuracy of single-tree volume
Using the measurement methods to obtain tree height	(1) DBH–height-based equation by using a telescopic pole vs. using reference height (2) DBH–height-based equation by using Lidar-derived height vs. using reference height	Understanding the impacts of different tree height measurement methods on calculation accuracy of single-tree volume

Note: DBH, diameter at breast height.

3. Results

3.1. Comparative Analysis of Tree Heights Measured Using Different Approaches

The comparative analysis of tree heights from different measurement methods indicated that the Lidar-derived tree heights were much closer to the reference heights than the measurements using the telescopic pole. As shown in Figure 2, the Lidar-derived tree height had an R^2 value of 0.95 compared with only 0.65 using the telescopic pole for Masson pine, and 0.99 vs. 0.93 for eucalyptus, implying the advantage of using UAV Lidar over a telescopic pole. One important finding shown in Figure 2 is that underestimation was obvious using the telescopic pole as the tree height increased, especially when the tree height was greater than 18 m (the maximum length of the telescopic pole), implying that the individual-tree volume was underestimated when using the conventional tree height measurement method, while using UAV Lidar data could avoid this problem.

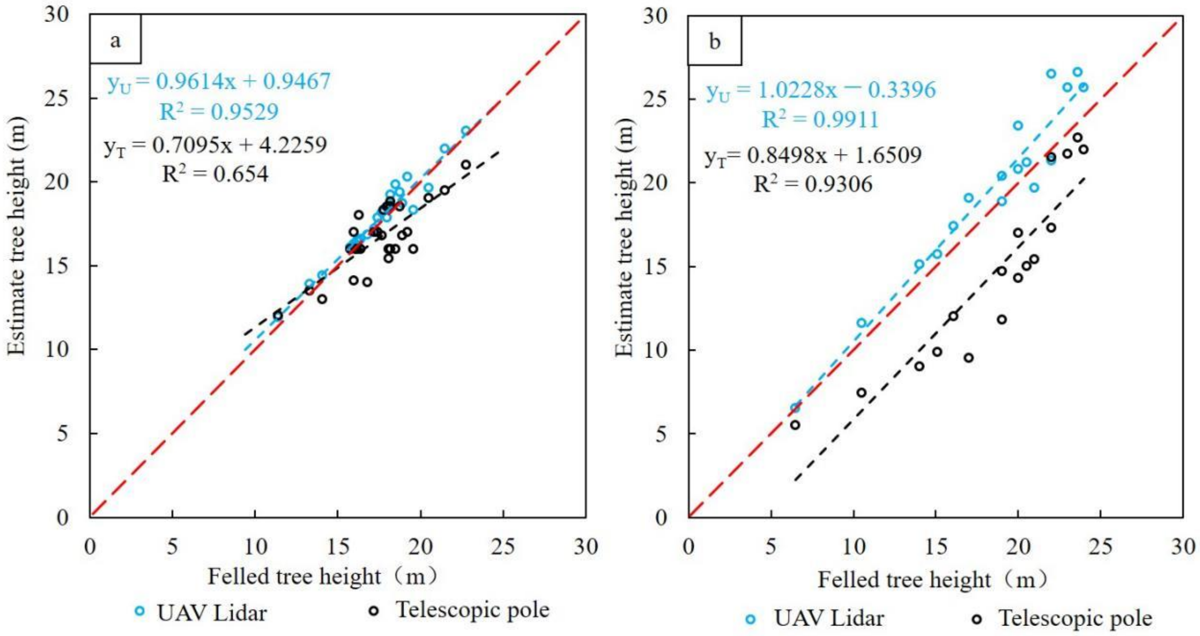

Figure 2. Relationship between reference data and estimated heights using Lidar and a telescopic pole for Masson pine (**a**) and Eucalyptus (**b**).

Quantitative comparison of bias and RMSE (Table 4) indicated that the tree height using a telescopic pole was underestimated by 4.8% for Masson pine and 6.7% for eucalyptus, while the tree height using UAV Lidar was slightly overestimated by 1.6% and 0.6%, respectively. Overall, the RMSE was 1.6 m for Masson pine and 2.0 m for eucalyptus using a telescopic pole, while the RMSE was reduced to approximately half a meter for both tree species using UAV Lidar. The results imply the advantage in using UAV Lidar over a traditional tree height measurement approach. Table 4 also indicates that eucalyptus had higher measurement errors than Masson pine using a telescopic pole, but the inverse was true using Lidar data, implying that the crown sizes and shapes of different tree species may have affected the measurement accuracy, depending on the methods used.

Table 4. Evaluation of measured tree heights using different methods.

Forest Type	Number of Trees	Telescopic Pole vs. Felled Tree		Lidar vs. Felled Tree	
		Bias (m) (Bias%)	RMSE (m) (RMSEr%)	Bias (m) (Bias%)	RMSE (m) (RMSEr%)
Masson pine	30	−0.84 (−4.8%)	1.57 (9.0%)	0.27 (1.6%)	0.56 (3.2%)
Eucalyptus	17	−1.31 (−6.7%)	1.96 (9.9%)	0.11 (0.6%)	0.54 (2.7%)

Note: Bias%, relative deviation; RMSE, root mean square error; RMSEr, relative root mean square error.

The tree height was another factor influencing measurement accuracy. When trees taller than the length of a telescopic pole were measured, the uncertainty of the height was much higher than that of the shorter trees using a telescopic pole; however, the Lidar-based method provided robust tree height measurement with no significant difference in uncertainty between tall and short trees, as shown in Table 5. This situation implies the advantage in using Lidar data over a telescopic pole (Tepo in Table 5), especially for tall trees.

Table 5. Evaluation of measured tree height results based on different height ranges.

Height Range (m)	Masson Pine				Eucalyptus			
	Lidar vs. Felled Tree		Tepo vs. Felled Tree		Lidar vs. Felled Tree		Tepo vs. Felled Tree	
	RMSE (m)	RMSEr (%)	RMSE (m)	RMSEr (%)	RMSE (m)	RMSEr (%)	RMSE (m)	RMSEr (%)
≤18	0.33	2.1%	1.05	6.6%	0.30	2.28%	0.96	7.26%
>18	0.76	3.9%	2.06	10.7%	0.61	2.70%	2.25	10.0%

Note: RMSE, root mean square error; RMSEr, relative root mean square error; Tepo, telescopic pole.

3.2. Impacts of Different Allometric Equations on Calculation Accuracies of Single-Tree Volumes

Because double-entry models usually produce more accurate volumes than single-entry models, we took the volumes from the DBH–height-based models as references for comparisons (Table 6). The results show that the DBH-based models underestimated the tree volumes by 0.071 m^3 for Masson pine and 0.034 m^3 for eucalyptus; the corresponding relative errors were 21.18% and 23.86%, while the RMSEr were 24% and 33.9%, respectively. This situation implies the preference for using DBH–height-based models for tree volume calculation.

Table 6. Comparison of single-tree volumes based on different allometric equations.

Forest Type	Number of Trees	Bias (m^3) (Bias%)	RMSE (m^3) (RMSEr (%))
Masson pine	35	−0.071 (−21.18%)	0.081 (24.04%)
Eucalyptus	50	−0.034 (−23.86%)	0.048 (33.90%)

Note: Bias%, relative deviation; RMSE, root mean square error; RMSEr, relative root mean square error.

The comparison of individual-tree volumes indicates that the volumes from the DBH-based and DBH–height-based models had a strong linear relationship for both species (Figure 3), but the volumes from the DBH-based model were lower than those from the DBH–height-based models, and the discrepancies became larger as the volume increased, especially when the volume was greater than 0.45 m^3 for Masson pine (Figure 3). The strongly linear relationship in Figure 3 indicates that a simple linear regression model can be developed to calibrate the tree volume resulting from the DBH-based model, as expressed in Equations (3) and (4).

$$Y_{mp} = 1.1748x + 0.0249, \qquad r^2 = 0.96 \tag{3}$$

$$Y_{eu} = 1.3119x + 0.0002, \qquad r^2 = 0.99, \tag{4}$$

where Y_{mp} and Y_{eu} are the calibrated volume values of Masson pine and eucalyptus, and x is the volume from the DBH-based model. When the volume was relatively small, for instance, less than 0.45 m^3, the simple regression model could effectively calibrate the underestimation problem caused by the DBH-based model. However, when the volume was higher, here greater than 0.45 m^3, as shown in Figure 3, the calibration effect became poor because of the high variation in volumes. This implies the need to use DBH–height-based models for tall-tree volume estimation.

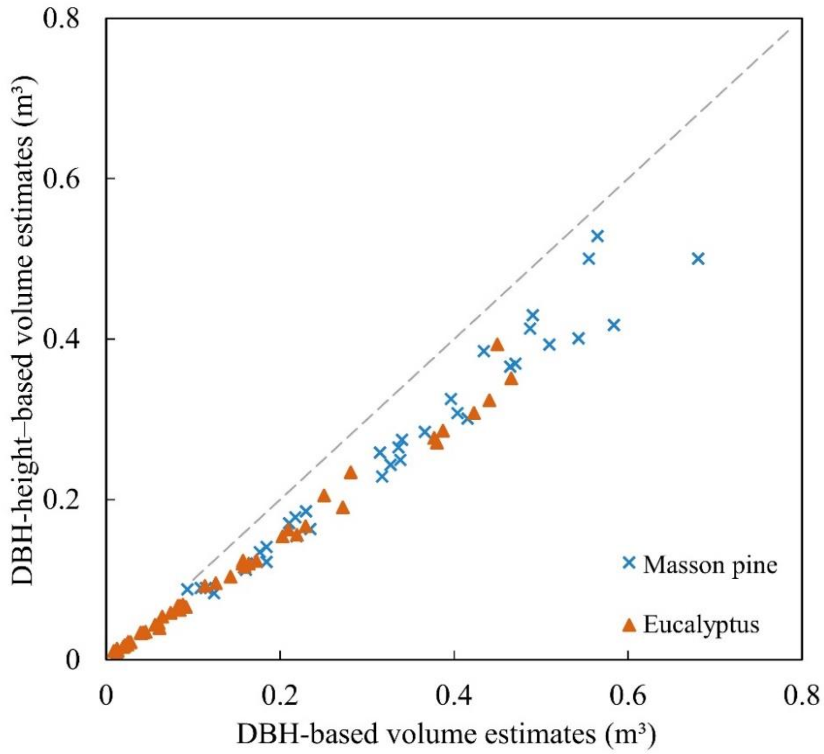

Figure 3. Comparative analysis of single-tree volumes from different allometric equations.

3.3. Impacts of Tree Height Measurement Approaches on the Calculation Accuracies of Tree Volumes

Comparison of individual-tree volumes calculated using DBH–height-based model and the heights measured by different approaches (Table 7) indicates that the single-tree volume was underestimated by 4.9% for Masson pine and 6.7% for eucalyptus using the tree height from a telescopic pole, but it was overestimated by 1.4% and 0.9%, respectively, using the tree height from the Lidar data. Overall, the RMSEr was 9.1% and 11.8% for Masson pine and eucalyptus, respectively, using a telescopic pole, but it decreased to only 3.4% and 2.4% using the Lidar-derived tree height, implying that the improved tree height measurement accuracy could considerably reduce tree volume estimation errors.

Table 7. Evaluation of single-tree volume results based on different tree height measurement methods.

Forest Type	Number of Trees	Telescopic Pole vs. Felled Tree		Lidar vs. Felled Tree	
		Bias (m^3) (Bias%)	RMSE (m^3) (RMSEr%)	Bias (m^3) (Bias%)	RMSE (m^3) (RMSEr%)
Pine	30	−0.014 (−4.9%)	0.025 (9.13%)	0.004 (1.36%)	0.010 (3.40%)
Eucalyptus	17	−0.012 (−6.66%)	0.021 (11.81%)	0.002 (0.86%)	0.004 (2.35%)

When the telescopic pole was used for measuring tree height, tall trees had much higher volume estimation errors than shorter trees (e.g., lower than the length of the telescopic pole) (see Table 8), but the Lidar-based height did not have this problem, implying the advantage of using Lidar technology to estimate tree volumes over the conventional tree height measurement method.

Table 8. Evaluation of single-tree volume results based on different height ranges.

Height Range (m)	Masson Pine				Eucalyptus			
	Lidar vs. Felled Tree		Tepo vs. Felled Tree		Lidar vs. Felled Tree		Tepo vs. Felled Tree	
	RMSE (m^3)	RMSEr (%)	RMSE (m^3)	RMSEr (%)	RMSE (m^3)	RMSEr (%)	RMSE (m^3)	RMSEr (%)
≤18	0.005	2.31%	0.011	5.14%	0.001	2.19%	0.003	6.82%
>18	0.013	3.59%	0.036	9.9%	0.005	2.12%	0.024	10.70%

Note: RMSE, root mean square error; RMSEr, relative root mean squatter error; Tepo. telescopic pole.

4. Discussion

4.1. The Importance of Obtaining Accurate Tree Heights

Tree height and DBH are two critical factors used in allometric equations, thus, their measurement accuracies directly affect the calculation accuracy of single-tree volumes. In general, DBH can be measured accurately in the field, but tree height measurement is challenging, especially for tall trees with large crown sizes and in dense tree canopies in mountainous regions [43]. Conventional tree height measurement using a telescopic pole can provide accurate height values when trees are relatively short [44,45]. However, when trees are taller than the measuring tool, the estimated height values may have large uncertainties, as shown in our research: the RMSEr was over 10% when the tree heights were greater than 18 m. In addition, using a telescopic pole to measure tree height in the field is time-consuming and labor-intensive, especially in mountainous regions with dense canopies and steep slopes. The crown sizes and shapes of different tree species also affect measurement accuracy using a telescopic pole because of the difficulty in judging treetops from the ground. Alternatively, UAV Lidar data provide much more accurate tree height values, especially in sites where field measurements are difficult to implement. The top-down measurement makes up for the disadvantages of the conventional tree measurement method. Lidar data can quantitatively and accurately determine the sizes of individual treetops.

Our research shows that UAV Lidar data provided tree heights with an RMSE of 0.54–0.56 m, relatively high errors compared to what some previous research reported [46,47]. The main reason includes the DEM quality and identification accuracy of individual trees due to the point cloud density. A point cloud density of about 40 pt/m^2 can effectively estimate the tree height of a single tree but may not be sufficient for obtaining precise DEM for sites with dense understories. A high density of point clouds may be needed for dense forests to accurately capture DEM. Another reason may be the underestimated heights of felled trees due to ignoring the stump height and the broken treetops for some felled trees.

We have shown that UAV Lidar data can accurately and effectively measure tree heights and has advantages over the conventional telescopic pole method; for instance, it is not affected by different kinds of tree species with various crown sizes and shapes. However, measuring tree DBH, which is critical for volume estimation, is difficult with UAV Lidar [48]. The synergy of UAV Lidar and terrestrial laser scanning (TLS) data may provide a new way to obtain the parameters of individual trees, because TLS can accurately measure tree DBH, while UAV Lidar can provide more accurate tree heights, especially for tall trees. The adoption of UAV and TLS in forest inventory can facilitate the rapid and accurate retrieval of forest parameters and reduce fieldwork but may raise the cost due to the expensive Lidar equipment. More research is needed to explore the integration of UAV Lidar and TLS data to accurately extract single-tree attributes.

4.2. The Importance of Using DBH–Height-Based Allometric Equations to Improve Tree Volume Calculation Accuracy

Forest inventories based on sample plots generally use a DBH-based model to calculate the tree volume because of the difficulty in measuring tree height in forest sites [10]. Previous research has indicated that the use of improper allometric equations for biomass or growing stock volume estimation may account for 30–70% of the total uncertainty, and is the primary error source [49,50]. For instance, using a DBH-based model to estimate Chinese fir volume yields a relative error between 32% and 60% for individual trees, and between 34% and 34% for sample forest stock volume [13]. Our research also confirmed this big difference between using DBH-based and DBH–height-based models and indicated the necessity of using DBH–height-based models if accurate tree height data are available.

The relationship between DBH and volume is closely related to tree characteristics such as species, age, and density in a unit and external factors such as soil and terrain conditions, all of which affect tree growth. Different sites have various influences on DBH and height growth. For instance, two trees of a specific tree type with the same DBH could have different height growths due to one growing on a mountain ridge or summit and the other one growing in a valley or at the foot of the mountain. Because of the difference in site indices in a large area, the same DBH-based model may produce high uncertainties if it is applied directly to different regions. However, the DBH–height-based model can considerably reduce this problem because of the improved relationship between volume and DBH-height. In reality, DBH–height-based models have not been extensively employed for tree volume calculation. The major reason is the difficulty in precisely measuring tree height in forested regions, in addition to the intense labor requirement and high measurement errors. As UAV technology is gradually being used more in forest inventories, tree height can be more precisely and easily obtained than with conventional tree measurement approaches; thus, the use of DBH–height-based models will be common in the future. Our research indicates the necessity of using the DBH–height-based models, in particular, when individual-tree volume is relatively high.

5. Conclusions

This research selected two typical sites in a subtropical region of China to examine the impacts of tree heights and allometric equations on tree volume calculation accuracy for Masson pine and eucalyptus. The tree height measurements of felled trees were used as reference data to evaluate the measurement accuracy of a telescopic pole and UAV Lidar data, indicating the importance of using UAV Lidar technology to obtain accurate tree height. In particular, UAV technology has advantages over telescopic poles in forest sites with complex forest stand structures. The comparison of the DBH-based and DBH–height-based allometric equations showed the necessity of using a DBH–height-based model for tree volume calculation, especially for tall trees. This research shows that the DBH-based model underestimated tree volume by 23.77% for Masson pine and 33.84% for eucalyptus. UAV technology provides a new tool for reducing this uncertainty, which is a critical data source for forest biomass and carbon studies. More research is needed in combining TLS and UAV Lidar data to accurately extract tree parameters without the onus of in-field measurements.

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