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yuan sun (✉ sunyuan1123@126.com)

Nanjing Forestry University <https://orcid.org/0000-0002-4595-9237>

XiuYun Lin

Nanjing Forestry University

Yulin Gong

Nanjing Forestry University

Jiawen Jiang

Nanjing Forestry University

Yanli Zhang

Stephen F Austin State University

Xiao Rong Wen

Nanjing Forestry University

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Analysis of Dynamic Forest Structures Based on Hierarchical Features Extracted from Multi-station LiDAR Scanning

Yuan Sun^{1,2}, Xiuyun Lin¹, Yulin Gong¹, Jiawen Jiang¹, Yanli Zhang³, Xiaorong Wen^{1,2}

¹ Co-Innovation Center for Sustainable Forestry in Southern China, Nanjing Forestry University, Nanjing 210037, China; sunyuan1123@126.com; 18771042269@sina.cn; sunyhot23@hotmail.com

² College of Forestry, Nanjing Forestry University, Nanjing 210037, China

³ Arthur Temple College of Forestry and Agriculture, Stephen F. Austin State University, Nacogdoches, TX 75962, USA zhangy2@sfasu.edu

* Correspondence: yuan.sun@njfu.edu.cn; Tel: 0086-18205171887

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Abstract: *Background:* The rapid development of active remote sensing laser scanning technology has led to the accumulation of substantial data on long-term forest changes. Accurate selection of the key parameters from larger amounts of cloud data is a prerequisite for volume estimates of standing trees. This study collected three phases of data over 5 years from *Liriodendron chinense* plantation forest. A series of the height-related characteristic parameters was extracted from the scanned points of each tree stem, which includes a novel feature of the height cumulative percentage (Hz%) proposed by us. Meanwhile, taking the manually measurements directly from the terrestrial laser scanning (TLS) data as the ground truth, the performance of various models combined with the characteristic parameters on the prediction of the wood volume of each tree was evaluated for the purpose of determination of the optimal parameters and prediction models suitable for the tree species of *Liriodendron chinense*. *Results:* The shape of the upper tree trunk extracted by the point cloud is equivalent to that of the analytical tree with inflection points at 25% and 50% of the height. Among the correlations between the hierarchical features and volumes, the parameters with the highest correlations are H25 and H50. The hierarchical parameters were selected for volume modeling. H25 and diameter at breast height (DBH) were used for all three phases, for which the fitted R^2 reached 0.951, 0.957 and 0.901. The modeled dynamic volume change was highly correlated with the actual point cloud-extracted volume change. In the linear relation, the intercept is -0.081, and the slope is 1.14. *Conclusions:* The Hz% value provided by multi-station scanning was closely related to the characteristic stumpage parameters and could be used to invert the dynamic forest structure. The volume model based on point cloud hierarchical parameters could be used to monitor the dynamic changes in forest volume and provide an updated reference for applying TLS point clouds for the dynamic monitoring of forest growth information.

Keywords: Height Accumulative Percentage, Forest Structure, Dynamic Change, Terrestrial Laser Scan, Volume Model, *Liriodendron chinense*

1. Introduction

The application of light detection and ranging (LiDAR) for three dimensional (3D) modeling and mapping has a productive history in forest resource surveys[1]. LiDAR data has facilitated various landscape and plot-level applications ranging from the structure and distribution of forest to

the dynamic changes of forest resources [2-5]. Long-term dynamic monitoring and evaluation of forest growth and development constitute the main objectives and research directions of forest management [6]. Some investigations performed in the early 2000s explored the ability of terrestrial laser scanning (TLS) technology to measure forestland factors [7], [8]. Recent studies have shown that TLS is capable of accurately measuring the structural properties of live stumpage, such as the stem curves, which are difficult to directly measure by using conventional tools [9]. Moreover, inversions of the volume and biomass of individual trees and sample plots performed by using point cloud data have also been shown to have good estimation accuracy, and models established based on such data are similar to regional/national allometric growth models [10]-[12] .

Moreover, the remote sensing information of an object can be reflected in the characteristic parameters of its point cloud distribution[13]. Previous studies have shown that the characteristic parameters determined by laser radar can be employed to effectively invert the structural parameters of forests and thus have been widely applied [14]. For example, Næsset et al. (2002) used the height percentile and density characteristic parameters to invert the forest structural parameters dominated by *Picea jezoensis* and *Pinus densiflora*, and the results showed that the 90% height percentile can reliably predict most forest structural parameters[15]. In addition, Silva et al. (2016) predicted the accumulation of Eucalyptus plantation forest by using the height variation coefficient of the characteristic LiDAR parameters and the 99% height percentile [16]. Three-dimensional scanning offers a major advantage over two-dimensional color imaging because nuisance variables, such as the illumination conditions and small pose changes, exert relatively small influences on the observations. In research on face recognition, facial surfaces are represented using radial curves emanating from the tip of the nose and the elastic shapes of these curves are analyzed to develop a Riemannian framework; accordingly, full facial surfaces can be evaluated [18]-[19]. Trees also have a curved shape, named the stem curve, which forms a taper [9]. The point cloud density can accurately reflect the spatial distribution of tree trunks from top to bottom, and the TLS has shown considerable promise in obtaining highly accurate estimates of the tree diameter, height, and stem curve.

Multi-station scanning and stitching are used with TLS to obtain stumpage information, which could be concentrated in a small area, to obtain more detailed information about the lower vegetation structure of a forest [20]. The spatial resolution (point density) of TLS data also differs significantly with different tree heights due to variations in the fixed (static) setting and scanning mode for the scene [21]. Therefore, in terms of the data size and geometric complexity, the segmentation of characteristic TLS parameters offers different advantages over that of ALS parameters [5]. Modes can already be established with mature methods by extracting the structural parameters of stumpage using point cloud coordinate information [22]. However, few studies have extracted the structural parameters of stumpage by applying the distribution characteristic parameters of ground point clouds of measured objects. The recovery modes of TLS beams can be divided into two types: single-echo mode and multi-echo mode. The multi-echo technique uses the light spot sizes to divide the waveform. Partial wave information can be obtained on both the surface and the edge of the measured object, and echoes can be divided multiple times; therefore, multi-echo data can contain more complete information about the tree crown and greatly increase the number of point clouds, and thus the quantity of information acquired by the scanner [23]. Such echoes have been applied and researched in Europe since 2013 [24], particularly to evaluate the differences between multi-echo and single-echo scanners in mountainous areas with dense vegetation, and the results showed that TLSs with multi-echo abilities can provide more detailed digital terrain model (DTM) data in areas with dense vegetation. Moreover, some Chinese scholars proposed that the multi-echo feature could be used to improve measurements of canopy gaps [25] .

Similarly, the scanning modes of TLS are divided into two types: single-station scanning mode and multi-station scanning mode. Different scanning modes have an important influence on the extraction of data parameters from a sample plot. If the laser does not penetrate, single-station

scanning can obtain structural information only for the surface of the object in one direction while multi-station scanning can compensate for these missing data [26]–[27]. Acquiring the appropriate number of TLS sites involves a trade-off between the cost of field work (in terms of time and expense) and the quality of data based on the field scanning experience. However, multi-station scanning is widely believed to effectively reduce occlusion; furthermore, multiple scanning point clouds can be integrated into one unified coordinate system, and multiple scanning points can be used to integrate three-dimensional information [28]. According to the latest experimental results from the Finnish Geodetic Institute (FGI), multi-station scanning greatly improves the average accuracy of parameter extraction (the single-station scanning accuracy in moderately dense sample plots was less than 64%, and the accuracy in highly dense sample plots was as low as 31%). However, the multi-station scanning accuracy for moderately dense sample plots was 74%, and the accuracy in highly dense sample plots reached 53% [6].

Therefore, a multi-station scanning method was used in the study to obtain complete information about the stumpage diameter, tree height and vertical distribution of the tree crown. An algorithm for extracting the brand new hierarchical characteristics of TLS point clouds was designed. Then, models corresponding to the measured stumpage characteristics were developed to establish a volume model based on the characteristic parameters by using data in three periods to provide a reference for applying TLS in monitoring dynamic forest changes.

Fig. 1 Technical process

2. Materials and Methods

2.1 Study site and data collection

The study site was located within the Experimental Forest of Nanjing Forestry University to the west of Wuqi Hill in Jiangsu Province, China. The annual average temperature is 15.5 °C with a maximum of 29 °C in summer and a minimum of 2 °C in winter. The average elevation and slope are approximately 150 m and 20°, respectively. The yellow brownish soil is approximately 60 cm thick and has a gravel content of 20% and surface humus content of 1.5%. An even-aged forest of

Chinese tulip trees (*Liriodendron chinense*) was planted with a spacing of 3 m × 3 m in March 1981, and the sample plot has dimensions of 40 m × 25 m.

The point cloud data of the sample plot were collected in three phases in winter in January 2014, 2018 and 2019, when the trees were leafless. The artificial forest had very little undergrowth and therefore is appropriate for research using TLS. A Leica Scan Station C10 was used in 2014, where the scanning angle was set to 270° vertically and 360° horizontally, and the scanning rate was 50,000 dots./second. In 2018 and 2019, a Riegl VZ-400i laser scanner with an original digital echo, real-time waveform processing and multi-beam transceiver processing technologies was used, and it is capable of accepting infinite echoes with scanning angles of 100° vertically and 360° horizontally and has a scanning rate of 500,000 dots./second.

At the same time, inspected sample data were obtained by conducting a manual inventory of each standing tree. In the inventory, the tree height was measured by a Leica D810 altimeter, the diameter at breast height (DBH) was measured with a diameter ruler, and the crown width was measured with a tap. In the first sampling period of 2014, two analytical trees were selected for the test sample data: the fifth tree in row 5 (DBH of 29.2 cm) and the seventh tree in row 7 (DBH of 33.1 cm). Figure 2 shows a schematic of the distribution of Chinese tulip trees at the sample site in 2014, 2018 and 2019, and the gray squares represent the locations of the trees utilized for stem analysis in 2014.

To obtain complete information regarding the vertical forest of standing timber, this study employed manual identification and subsetting to position and segment each tree to facilitate the subsequent extraction of the standing timber parameters.

Fig. 2 Sketch of the tree distribution in the study area

2.2 Data method

The sample plot was scanned at multiple stations, and all data were merged together through registration and splicing. Then, all points were imported into the same three-dimensional coordination system [28]. The stitching precision was 0.0045 m in 2014 and 0.0038 m in 2018 and 2019. LiDAR360 v2.2 was used to extract the digital elevation model (DEM) and carry out the

normalization procedure. Because the trees were leafless, the degree of overlap between individual tree point clouds obtained at the canopy level was almost negligible. Consequently, the crown of each individual tree could be clearly identified from the top view of the sample plot data. To obtain complete information of the vertical stem structure, individual trees were located and segmented by manual identification and cutting to facilitate the extraction of stem parameters.

2.2.1 Extracted tree height

To extract the tree height of each tree obtained by manual recognition and subsetting, the height of a single tree was calculated by the point cloud height difference, which is the difference in the peak cloud height of a single tree minus the height of the ground point cloud, as shown in formula (1).

$$H = Z_{\max} - Z_{\min} \quad (1)$$

2.3.2 Extracted diameters at various heights

The DBH is the primary structural feature for a standing tree together with the upper diameter along the tree trunk. Based on the single tree point data, three-dimensional point cloud data were converted into two-dimensional point cloud data; then, the least squares method was used to fit each circle to extract the diameter at a specific height. First, the data pertaining to single trees were sliced. Because excessively thin slices of point cloud data will result in insufficient data for calculating the diameter while overly thick slices will reduce the extraction efficiency [9]. This study controlled the slice thickness at 0.1 m. Rings were sliced at intervals of 1 m through the trunk, as shown in Figure 3. Then, the least square method was used to fit the diameter of the upper part of the stem.

Let $\{(x_i, y_i \mid i=1, 2, \dots, n)\}$ be the set of points to be determined in the data distribution. If (a, b) are the center coordinates of the circle and r is the radius, then the equation of the circle is as follows:

$$(x-a)^2 + (y-b)^2 = r^2 \quad (2)$$

From equation 2, the coordinates of the circle center (a, b) and the radius r can be calculated. If (x_i, y_i) is a discrete point in the point cloud dataset, then the distance between this point and the center of the circle is r_i . Taking this point as the center of the circle and r_i as the radius, the area of the circle is S_i . If the area of the fitted circle is S , then the area error is as follows:

$$\delta_i = S_i - S = \pi \left[(x_i - a)^2 + (y_i - b)^2 - r^2 \right] \quad (3)$$

According to the principle of least squares, the optimization objective function is as follow:

$$Q(a, b, r) = \min \quad (4)$$

In the above formula, Q is a function of a , b and r ,

Using the extremum function method can make Q obtain the minimum value; thus

$$\delta_Q \delta_a = \delta_Q \delta_b = \delta_Q \delta_r = 0 \quad (5)$$

The coordinates (a, b) and radius r of the center of the circle can be solved accordingly.

a) Full point cloud side view b) Trunk data after manual subsetting c) Slices of the upper diameter

Fig. 3 Schematic diagram of extracting slices from the upper diameter of a single tree

2.2.3 Obtaining the volume of each tree

Through the method mentioned above, the research obtained three stages of point clouds of each tree along the tree height. The number of points is shown in Table1.

Table 1 Number of points for three stages

	2014	2018	2019
Total points	19211863	19674289	1450978

The area segment quadrature method was used to calculate the standing timber volume of the central section of each tree [29]. According to the previous step, the central diameter of each segment was extracted, and the remaining segment (less than 2 m) was treated as the tip of the tree. The stem volume of each Chinese tulip tree (*L. chinense*) in the sample plot could be calculated with equation 6:

$$V = l \sum_{i=1}^n g_i + \frac{1}{3} g' l' \quad (6)$$

where V is the stem volume, g_i is the cross-sectional area of each segment, l is the length of the segment, g' is the cross-sectional area of the tip, l' is the length of the tip, and n is the number of segments.

2.2.4 Point cloud hierarchical characteristic analysis

Although point cloud density features can accurately reflect the state of the target spatial distribution, most density features are based on plane density analysis, which cannot fully reflect the real density characteristics of three-dimensional point clouds. From a hierarchical view of the point cloud of a standing tree, this research proposed the concept of the height cumulative percentage ($H_z\%$) of the point cloud to study the association of $H_z\%$ with other important forest resource parameters, such as the stem volume.

$H_z\%$ represents the cumulative total height ($z\%$) of all points in the cloud at a lower or equal height. Before calculating $H_z\%$, the point cloud of each individual tree should be normalized (with the DEM as the ground datum) and then sorted according to each point's height. MATLAB 2014a was used to process the data and to calculate $H_z\%$ based on equations 7 and 8:

$$H_z = h_m \quad (7)$$

$$z\% = \frac{\sum_{i=1}^m h_1 + h_2 + h_3 + h_4 + \dots + h_i}{\sum_{i=1}^n h_1 + h_2 + h_3 + h_4 + \dots + h_i} \times 100\% \quad (8)$$

where n is the total number of points for the point cloud of a tree and h_i is the height of point i . m denotes the number of points at which equation 8 is balanced, and h_m is assigned to $H_z\%$. Taking the tree in Figure 4 as an example, the total number of data points in the point cloud is 189,648, and the summed height of all points is 2,269,368 m. The height h_m of point m is 25.28 m, which accounts for 75% of the total cumulative height; therefore, $H_{75}=h_m=25.28$ m.

Fig. 4 Example of the height cumulative percentage ($H_z\%$)

Other hierarchical features of the point cloud, such as the mean height (Ht mean), standard deviation of the height (Ht std dev), variance of the point cloud height (Ht var), quartile of the height (Ht IQ), average absolute deviation of the height (AAD) and median absolute deviation from the median height (MAD), were also extracted as candidate variables for the subsequent stem volume regression (Table 2).

Table 2 Point cloud characteristic variables

Characteristic Variable	Description
Ht mean	Average height of the cloud point above the ground
Ht std dev	Standard deviation of the point cloud height
Ht var	Variance of the point cloud height
Ht IQ	Quartile distance of the point cloud height
AAD	Average absolute deviation
MAD median	Median absolute deviation from the overall median

Among these characteristic variables, they are $AAD = \frac{\sum_{i=1}^n |h_i - \bar{h}|}{N}$,

$Ht \text{ stddev} = \sqrt{\frac{1}{N-1} \sum_{i=1}^n (h_i - \bar{h})^2}$, and $Ht \text{ Var} = \frac{\sum_{i=1}^n (h_i - \bar{h})^2}{n}$ (where n is the number of points in the point cloud of a tree, h_i is the height of point i , and $\bar{h}$ is the mean height of all points)

2.3 Modeling and verification

To find the most suitable parameters for the volume model, the linear equation form shown in formula (9) was employed. According to the number of selected parameters, the formula was extended to obtain a unary primary volume model and a binary primary volume model [30]. Hence, three types of models were established. First, $H_z\%$ and DBH were taken as variables to conduct the modeling. Second, volume modeling was carried out by taking $H_z\%$ as the lone variable. Third, $H_z\%$ and other hierarchical features were modeled as variables.

$$V = a_0 + a_1x_1 + a_2x_2 + \dots + a_jx_j, j=1\dots m \quad (9)$$

Pearson's correlation coefficient (P) was calculated between each extracted feature parameter and volume (V). Feature parameters with a P value larger than 0.6 were selected and used as candidate variables for the volume model [6]. The parameters were calculated by using the multivariate stepwise regression of SPSS19 software, where the significance level of the model parameters was set as 0.05, and the equations with high collinearity were eliminated by using the variance inflation factor (i.e., $VIF > 10$) variable by using the variance inflation factor (VIF).

Then, the binary volume equation [29] was applied as a reference model (Formula 10) to establish the volume model based on the regression relationship between the DBH and tree height. This model reflects that certain stem characteristics have extensive regional applicability. DPS 17.1 software was used for the modeling and parameter estimation.

$$V = a_0(DBH)^{a_1}(H)^{a_2} \quad (10)$$

where V is the volume value, a_i denotes the coefficients, and x_i represents the independent variables of the equation.

To evaluate and verify the models, the coefficient of determination (R^2), root mean square error (RMSE) and F value were utilized as the evaluation indices for the model. The computation formulas are as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2}, \quad i=1, \dots, n \quad (11)$$

$$RMSE = \sqrt{\left(\frac{1}{n-1}\right) \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (12)$$

$$F = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y}_i)^2}{m} / \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n-m-1} \quad (13)$$

In the above formulas, y_i is the measured value, $\bar{y}_i$ is the measured mean value, $\hat{y}_i$ is the value predicted by the model, n is the number of samples, and m is the number of parameters in the equation.

The 10-fold cross-validation method was used to verify the prediction effect of the model. All individual tree data used for the modeling were randomly divided into n subsamples under the condition that the prediction model parameters had already been determined. One subsample was randomly selected as verification data (to be used in the subsequent fitting model for validation), while the remaining (n - 1) samples were used for training. The results were verified with 10 iterations, each subsample was validated once, and the mean value of n results was obtained as the estimated value of the model [31]. The prediction accuracy of the model was verified by building a scatter plot between the estimated values of the model and the TLS-extracted values.

Dynamic changes in the volume of the Chinese tulip tree were analyzed based on the data from the three periods. The volume of stumpage in the three periods was acquired by using the characteristic parameter volume prediction model, and the dynamic change in the volume was

calculated according to the diameter classes. The changes were compared with the actual volume change computed by the point cloud, and the feasibility of applying the inverted volume prediction model to analyze the dynamic changes in timber volume was evaluated.

3 Results and Analysis

3.1 Verification of the extraction with stem analysis

First, the extraction of the upper diameter should be confirmed. Data from the two analytical trees are shown in Figure 5 in a scatter plot of the upper diameters extracted from the point cloud and the corresponding diameters of the analytical trees. The extracted values have a high correlation ($R^2=0.9864$) with the measured values and show no significant difference. Accordingly, the following features extracted from the point cloud can be researched.

Fig. 5 Regression analysis of the extracted and analytical measured diameters

Then, data from the stem analysis were used to draw the taper curves as shown in Figure 6 b and d. Tree heights of 10 to 20 m represent the inflection points of the tree trunk. The point cloud data for these two trees were also drawn as shown in Figure 6 a and c. $H_z\%$ clearly increases with increasing height and reaches approximately 10 m of the tree height at 25%, which appears to be an inflection point; then, $H_z\%$ reaches approximately 20 m of the tree height at the value of 50%, which appears to be another inflection point and is followed by a gentle increasing trend for $H_z\%$.

Fig. 6 Comparative analysis of the height cumulative percentile and analytical tree stem curve
(a and c: $H_z\%$ versus height; b and d: analytical wood stem curve)

3.2 Features extracted from the point cloud data in three periods

Following the methods above, this research extracted the tree structure parameters (DBH and tree height) and hierarchical features ($H_z\%$ and H_{mean}) and counted the volume of each standing tree in all three periods. A summary of the stumpage features after normalization, denoising, extraction and calculation is shown in Table 3. The average DBH of a single tree increased significantly, and the average annual growth was stable at 0.3 cm. The standard deviation of DBH growth was large: 5.95 in 2014, 6.49 in 2018, and 7.66 in 2019. The tree height and volume also increased annually. The average heights of H_{75} , H_{55} , and H_{25} , which refer to the spatial distribution of tree trunks from top to bottom, decreased annually in accordance with the law of tree growth.

Table 3 Summary of features of a single tree in the three periods

Period		DBH (cm)	Tree height (m)	Volume (m ³)	H_{75}	H_{50}	H_{25}	H_{mean}
2014	range	14.21-42.58	17.11-32.40	0.13-1.75	11.98-29.72	18.96-26.84	14.18-20.13	1.84-26.64
	mean value	25.96	28.30	0.69	24.51	20.51	11.44	15.65
	standard deviation	5.95	3.52	0.36	11.45	7.76	3.56	8.88
2018	range	15.21-45.04	17.53-34.32	0.14-1.96	12.59-30.79	7.75-27.99	4.98-19.57	4.09-28.70
	mean value	27.52	29.73	0.77	23.49	18.53	9.41	16.61
	standard deviation	6.49	3.93	0.40	12.1	7.51	2.93	9.24
2019	range	15.83-45.61	17.67-35.00	0.15-1.98	9.22-22.02	7.22-17.07	2.92-8.96	2.71-26.33

mean value	27.87	30.12	0.80	15.29	10.47	5.55	10.93
standard deviation	7.66	4.08	0.44	3.02	5.32	10.08	12.73

3.3 Tree volume modeling results

A Pearson correlation analysis was conducted on individual trees, and the relationships between the tree height, DBH and hierarchical features with the tree volume determined by the point cloud data are shown in Table 4. According to the values from the point cloud data in the three periods, the DBH has the highest correlation with the tree volume, followed by the tree height, which conforms to the rule regarding the three elements of volume. Among the correlations between the hierarchical features and the tree volume, the highest correlation parameter in 2014 was H25, and then H50; the highest correlation parameter in 2018 was H25 and then H50; and the highest correlation parameter in 2019 was H80 and then H75. The various parameters involved in modeling the individual tree volume are listed in Table 4.

Table 4 Correlation analysis of individual plant parameters and volume

2014		2018		2019	
Parameter	Correlation	Parameter	Correlation	Parameter	Correlation
Structure	DBH	DBH	DBH	DBH	DBH
Parameters	Tree height	Tree height	Tree height	Tree height	Tree height
Hierarchical features	H25	H25	H25	H80	H7777
	H50	H50	H50	H75	0.7618
	Ht IQ	Ht IQ	Ht IQ	Ht stddev	0.7170
	AAD	AAD	AAD	H50	0.6500
	Ht mean	Ht mean	Ht mean	AAD	0.6289
	Ht var	Ht var	Ht var	Ht var	0.5055
	Ht stddev	Ht stddev	Ht stddev	MAD median	0.4967
	H75	H75	H75	Ht mean	0.2973
	MAD median	MAD median	MAD median	Ht IQ	0.2849
	H80	H80	H80	H25	0.1615

Thus, the volume model was established by using the hierarchical features DBH and tree height as variables. The model results are shown in Table 5. Among them, the binary volume models numbered 14-1, 18-1 and 19-1 are used as reference models and have the highest R^2 values (0.974, 0.974 and 0.919, respectively), and H and DBH are variables. The models numbered 14-2, 18-2, and 19-2 are also binary linear models with H25 and DBH as variables, and their R^2 values are 0.951, 0.957 and 0.901. Table 5 shows that the models with hierarchical features (H50, H80 and H75) have slightly lower R^2 values; however, these models seem to be better for predicting the volume, thus revealing the efficacy of $H_z\%$. In contrast, H25 is the first inflection point along the trunk.

Table 5 Results of the volume model for individual trees

Time	Models No.	Parameter and Coefficient	R^2	F value	RMSE/(m3)
2014	14-1	$v=0.106(DBH)^{2.035}(H)^{1.352}$	0.974	122.419	0.059
	14-2	$v=-0.795+0.021(H25)+4.847(DBH)$	0.951	570.604	0.083
	14-3	$v=-0.617+0.073(H50)-0.002(H80)$	0.707	69.961	0.199
	14-4	$v=-0.747+0.128(H75)-0.062(H80)$	0.612	45.690	0.229
2018	18-1	$v=0.247(DBH)^{2.018}(H)^{1.075}$	0.974	140.053	0.066
	18-2	$v=-0.928+5.655(H25)+0.016(DBH)$	0.957	661.538	0.086
	18-3	$v=-0.699+0.051(H50)+0.025(H80)$	0.712	72.799	0.219

2019	18-4	$v = -0.872 + 0.618(H75) + 0.009(H80)$	0.642	52.983	0.244
	19-1	$v = 0.734(DBH)^{2.002}(H)^{0.734}$	0.919	288.254	0.039
	19-2	$v = 0.062 + 0.092 \cdot H25 + 0.732 \cdot DBH$	0.901	233.182	0.140
	19-3	$v = 0.494 + 0.011(H75) + 0.008 \cdot H85$	0.632	28.642	0.274
	19-4	$v = -1.147 - 0.034(H50) + 0.156(H80)$	0.638	29.393	0.272

Models 14-2, 18-2, and 19-2 are used to predict the individual tree volume, and scatter plots that show the correlations between the model-predicted values and TLS values of the single tree volume in all three periods are drawn (Figure 7 a, b, and c). The plots reveal the precision of the models, which have relatively high R^2 values for 2019 (0.9603), 2018 (0.9501) and 2014 (0.869). All of the prediction lines are somewhat in accordance with the 1:1 verification line. Significant differences are not observed between the predicted and point cloud-extracted volumes. Therefore, the volume model with hierarchical parameters can be used as the volume model for each period.

Fig. 7 Scatter plots of the correlation between the volume model-predicted volume and TLS-extracted volume (a performs formula 2014-2, b performs formula 2018-2, and c performs formula 2019-2)

Then, the volume was counted for each DBH grade in each period, and the results are shown in Table 6. According to the previous steps, the volume of each tree was counted by the area segment quadrature method for the central section through the extracted point cloud data. The scatter plot in Figure 8 shows the variations in the modeled and TLS-extracted volumes. The linear relationship of the volume changes in the DBH grades between the modeled values and the values extracted from the point cloud was established and determined to have an intercept of -0.081, a slope of 1.14, and an R^2 of 0.98 (as shown in Fig. 8).

Table 6 Volume variations in DBH grades from 2014 to 2019

Diameter grade/(cm)	Number of diameter grade			Model -2 prediction/(m³)			Volume change 2018-2014/(m³)		Volume change 2019-2018/(m³)	
	2014	2018	2019	2014	2018	2019	Model -2	TLS measurement	Model -2	TLS measurement
10	2	0	0	0.32	0.00	0.00	-0.32	-0.29	0.00	0.00
15	10	9	8	2.76	2.06	1.92	-0.70	-0.44	-0.11	-0.12
20	13	9	8	7.36	5.81	5.35	-1.55	-2.41	-0.46	-0.78
25	19	15	14	15.28	13.59	12.78	-1.69	-2.03	-0.81	-0.49
30	13	18	15	15.34	21.47	22.67	6.13	6.97	1.20	1.53
35	2	3	8	3.61	6.34	8.11	2.73	2.88	1.77	1.30
40	1	0	1	1.14	0.00	1.60	-1.14	-1.75	1.60	1.65
45	0	1	1	0.00	1.40	1.73	1.40	1.96	0.33	0.31

Fig. 8 Linear relationship between the modeled volume and the point cloud-extracted volume

3.4 Dynamic analysis of the tree structure from features

3.4.1 Individual tree changes and the growth rate

Table 7 displays the individual changes in and growth rates of the tree height, DBH and tree volume in the three phases. Since the investigated periods spanned four years and one year, the growth rates are distinguished as four-years and one-year rates. The average rates of change among the three phases are as follows: tree height average growth rate of: 0.36–0.39 m; DBH average growth rate of 0.34–0.38 cm; and volume average growth rate of 0.02–0.03 m³. Among these rates, the average growth rate of the tree height is greater than the average growth rate in the four-year period of 2014–2018. Moreover, the volume growth rates in all three periods are relatively average.

Table 7 Growth rates of the features for individual trees in the three periods

	2014-2018		2018-2019		2014-2019	
	Growth rate in four years	Average growth rate	Growth rate in one year	Average growth rate	Growth rate in five years	Average growth rate
Tree height/(m)	1.43	0.36	0.39	0.39	1.82	0.36
DBH/(cm)	1.57	0.39	0.34	0.34	1.91	0.38
Volume/(m ³)	0.08	0.02	0.03	0.03	0.11	0.02

The variations in the diameter grades of the sample plot during the three periods are shown in Figure 9. The diameter step was 5 cm, and the initial diameter class was set to 5 cm. As the number of trees was counted by diameter class, the peak of the diameter distribution curve shifted from 25 cm in 2014 to 30 cm in 2018. Among the diameter classes, the shifted numbers of the 20 cm and 25 cm diameter classes were relatively high.

Fig. 9 Diameter grade distribution curves for 2014, 2018 and 2019

3.4.2 Height cumulative percentage analysis

As shown in Figure 10, the average $H_z\%$ of individual trees increases with the height in all three periods, with the first inflection point appearing at 25% (the height of the tree is approximately 10 m) with $H_z\% = 10$ m. The second inflection point appears at 55% (the height of the tree is approximately 20 m), with $H_z\% = 20$ m. These results indicate that the hierarchical features can reflect the change in the stem shape, and these features appear regularly within all five years. The height cumulative percentages of 25% and 55% for the Chinese tulip (*L. chinense*) tree are the two inflection points for standing trees. As evidenced, the cumulative height percentage of the point cloud can reflect the change in the stem shape.

Fig. 10 Average $H_z\%$ for individual trees in three periods

A comparison with Figure 6 shows the $H_z\%$ and stem shape variations, and the hierarchical feature clearly reflects the variation in the stem shape from the point cloud distribution with the tree height. Furthermore, 25% of $H_z\%$ is consistent with the periscope height.

4. Discussion and conclusions

First, before using laser technology, models of forest structures were established based on the DBH, tree height and tree volume in a conventional analysis[12]. Laser scanning technology provides data with high density point cloud that can be used to extract related geometric and statistical parameters for individual trees. The three-dimensional models reconstructed by the point cloud data reflect the vertical hierarchical structures of living trees. This study focuses on point cloud data obtained by TLS. After splicing, denoising and normalization, the point cloud data have a relatively uniform point distribution regardless of the type of equipment. Photogrammetry and ALS technology can also achieve the same data distribution [13]. Therefore, whether vertical hierarchical parameters can be used as fusion features for multi-source point cloud data is worthy of further discussion.

Second, this paper studied the potential of TLS by estimating the volume of *L. chinense* in the study area by using point cloud hierarchical and statistical parameters. These parameters changed with the growth characteristics, namely, the tree height and canopy diameter. Table 4 lists the correlations of these characteristic parameters in the data from three periods and shows that among the parameters, H50 and H25 were mostly correlated with volume. Table 5 shows the volume models. The accuracies of models 14-2, 18-2, and 19-2 were improved by adding height cumulative percentage ($H_z\%$) with the DBH factor. This paper proposed that the corresponding model could be chosen according to the actual needs of the investigation based on the species and the scanning condition. The structure of standing tree could be derived from point cloud data, and a dynamic analysis could be performed through modeling. The hierarchical parameters ($H_z\%$) for modeling can be easily obtained under the condition of satisfying the accuracy requirements (as shown in Table 5).

Third, the tree height is one of the three most important elements of the tree volume. Many studies have demonstrated that laser scanning data have an advantage in obtaining tree height [32] and that ALS waveform can be converted into the corresponding canopy height contour; thus, the height of each quantile can be calculated analogously in a sample canopy profile of the ground [21]. Studies on extracting high percentiles ($P\%$) based on Fusion software and establishing various structural models and biomass models [12] have been widely reported. However, TLS data have dense point clouds under the canopy and can obtain structures with precision. This research defined the new ground vertical characteristic parameter $H_z\%$, which is used to express the cumulative height of the first m points (from the bottom up to the first point) divided by all heights equal to $Z\%$ n points, with the first m point heights representing the $Z\%$ of H of the point cloud. This parameter extends the measurements of standing tree point clouds and extracts the characteristics reflecting the tree height and canopy from the vertical distribution features of point clouds. Whether this feature can reveal the trunk shape and whether $H_z\%$ is related to the planting density and species characteristics are worthy of further discussion. $H_z\%$ could also be discussed as a new taper parameter that can be obtained by laser scanning technology.

List of abbreviations:

LiDAR	Light Detection and Ranging
3D	three Dimensional
TLS	Terrestrial Laser Scanning
DEM	Digital Elevation Model
DBH	Diameter at Breast Height
$H_z\%$	Height cumulative percentage
Ht mean	mean Height
Ht std dev	standard deviation of the Height
Ht var	variance of the point cloud Height
Ht IQ	quartile of the Height
AAD	Average Absolute Deviation of the Height

MAD Median Absolute Deviation from the median Height

Ethics Declarations

Ethics approval and consent to participate: Not applicable.

Availability of data and materials: Not applicable.

Competing interests: The authors declare that they have no competing interests.

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Figures

Figure 1

Technical process

Figure 2

Sketch of the tree distribution in the study area

Figure 3

Schematic diagram of extracting slices from the upper diameter of a single tree a) Full point cloud side view b) Trunk data after manual subsetting c) Slices of the upper diameter

Total points (n) : 189648
The total points's height: 2269368 m
Cumulative height ratio is:

$$75\% = \frac{\sum_{i=1}^m (h_1 + h_2 + h_3 + h_4 + \dots + h_i)}{\sum_{i=1}^n (h_1 + h_2 + h_3 + h_4 + \dots + h_i)} \times 100\%$$

Where h_i is the height of the i-th point and h_m is the height corresponding to the m-th point

$$H_z = h_m = 25.28\text{m}$$

Figure 4

Example of the height cumulative percentage (Hz%)

Figure 5

Regression analysis of the extracted and analytical measured diameters

Figure 6

Comparative analysis of the height cumulative percentile and analytical tree stem curve (a and c: Hz% versus height; b and d: analytical wood stem curve)

Figure 7

Scatter plots of the correlation between the volume model-predicted volume and TLS-extracted volume (a performs formula 2014-2, b performs formula 2018-2, and c performs formula 2019-2)

Figure 8

Linear relationship between the modeled volume and the point cloud-extracted volume

Figure 9

Diameter grade distribution curves for 2014, 2018 and 2019

Figure 10

Average Hz% for individual trees in three periods