Estimation of Larch Growth at the Stem, Crown and Branch Levels Using Ground-based LiDAR Point Cloud

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Abstract

Tree growth is an important indicator of forest health and can reflect changes in forest structure. Traditional tree growth estimates use easy-to-measure parameters, including tree height, diameter at breast height, and crown diameter, obtained via forest in situ measurements, which are labor intensive and time consuming. Some new technologies measure the diameter of trees at different positions to monitor the growth trend of trees, but it is difficult to take into account the growth changes at different tree levels. The combination of terrestrial laser scanning and quantitative structure modeling can accurately estimate tree structural parameters nondestructively and has the potential to estimate tree growth from different tree levels. In this context, this paper estimates tree growth from stem-, crown-, and branch-level attributes observed by terrestrial laser scanning. Specifically, tree height, diameter at breast height, stem volume, crown diameter, crown volume and first-order branch volume were used to estimate the growth of 55-year-old larch trees in Saihanba of China, at the stem, crown and branch levels. The experimental results showed that tree growth is mainly reflected in the growth of the crown, i.e., the growth of branches. Compared to one-dimensional parameter growth (tree height, diameter at breast height, or crown diameter), three-dimensional parameter growth (crown, stem and first-order branch volumes) was more obvious, in which the absolute growth of the first-order branch volume is close to the stem volume. Thus, it is necessary to estimate tree growth at different levels for accurate forest inventory.

Keywords: tree growth, different tree levels, terrestrial laser scanning, quantitative structure model
1. Introduction

Forests play an important role in wood provision, climate regulation, and water conservation [1], and they act as carbon sinks and account for approximately 50% of the global biosphere [2]. As one of the indicators of forest health, tree growth is closely related to forest structure and global climate change [3-5]. In addition, tree growth can reflect the carbon sequestration capacity of the forest and changes in the regional climate, atmospheric environment, air quality, global carbon-water balance and soil nutrient cycling [6-8]. Therefore, the quantification of tree growth is very significant to the study of forest health and sustainable development. Accurately estimating tree growth can successfully improve the management of forest ecology, resources and plantations and is also the basis for analyzing tree growth correlations with genes, climate, environments and other factors [9].

Tree growth is defined as the increase in an individual tree in dimensions over time [2, 10]. It is generally estimated by the following two methods: growth changes in tree parameters over a period of time [11] or tree-ring series analysis after partial cutting [12, 13]. However, tree rings are generally obtained by logging and sampling from trunks, which is destructive and labor intensive [6, 14], and sampling in forests for tree-ring analysis records makes it difficult to ensure the representativeness of the samples [1]. In contrast, tree parameters are relatively easy to measure and are often used to estimate tree growth. For example, tree height and diameter at breast height (DBH) are two parameters often used to estimate tree growth [15, 16], which can describe tree growth radially and vertically [17] and are often used in tree growth model reconstruction [18]. In addition, parameters such as crown diameter, canopy projection area, tree volume and biomass were also used to estimate tree growth [19, 20]. Currently, tree height and DBH are widely used to quantify tree growth in research on the relationship among tree growth, the environment, forest management, etc. [20]. Therefore, accurate estimation of tree parameters is the key to quantifying tree growth.

Traditionally, tree parameter acquisition relies on forest in situ measurements, which are labor intensive and time-consuming [21] which is one of the main reasons why tree growth estimates are often estimated using easy-to-measure parameters or forest inventories [22]. With the development of modern science and technology, the "Talking Tree" was invented and used for tree growth monitoring, which can effectively solve the time-consuming and laborious problem of traditional tree parameters estimation. This device mainly monitors the growth changes of the tree diameter, such as the diameter of stem and branch, through the growth measurement ring. Therefore, “Talking Tree” can well monitor the growth of tree girth, but it cannot take the change of parameters into account, such as tree height, crown diameter and volume, and so on.

In recent years, with the development of remote sensing technology, images and point clouds have been widely used in forest inventories [23]. Based on unmanned aerial vehicle (UAV) and satellite images, forest canopy height [24] and biomass estimation [25, 26] can be nondestructively acquired and can promote tree growth estimations at a large scale [13, 27]. However, determining
accurate tree growth at the individual tree level is difficult [2] and other parameters, such as the DBH and crown diameter, are difficult to acquire. In contrast, as an active remote sensing method, light detection and ranging (LiDAR) technology can measure tree- and plot-level parameters with high accuracy [28, 29], and has been widely used for forest inventories [30-32]. In particular, terrestrial laser scanning (TLS) has solved the problem of time-consuming, labor-intensive traditional in situ measurements in forests [33] and can efficiently carry out repeated forest inventories, making it possible to estimate tree growth using different parameters [34]. Studies have shown that TLS can efficiently obtain high-precision tree parameters nondestructively and has the ability to characterize the stem form and volume allocation growth changes [35].

Compared with stem, the crown structure is complex, in which the branch structure is more difficult to quantify. As the main component of crowns, branches play an important role in the carbon balance of forest ecosystems, and studies have shown that the carbon loss from branch and trunk respiration is approximately 1/3 of the carbon consumption in forest ecosystems; moreover, branch respiration accounts for approximately 50% of the total annual respiration of the forest [36]. However, due to its complex structure, branch parameters are usually acquired by regression models, which are fitted based on the branch length, basal diameter [36] or crown parameters [37, 38] from in situ measurements in forests. It is also for this reason that the quantification of tree growth is rarely described using branch parameters.

However, few researchers have considered the difference in the growth rate of trees at different tree levels (such as stems, crowns and branches). In fact, different tree parameters have different growth rates at different ages, the increase in tree height will tend toward zero as the tree approaches maturity [2]. Although DBH and canopy projection area continuously increase during the whole growth period [2], the same increase in DBH has varied impacts on the biomass in trees of different sizes, especially for trees with large crowns. Volume and biomass are used as additional tree parameters to estimate tree growth in some studies [39, 40], which are difficult to acquire directly and usually derived from tree height and DBH based on allometric equations [41, 42]. Therefore, to avoid these problems, tree growth should be estimated using parameters from different tree levels at different forest ages. For example, Montoro Girona et al. [15] used tree height, DBH and canopy projection area to quantify tree growth, which can be viewed as tree growth estimations at the stem and crown levels. Pretzsch [4] estimated tree growth based on research over the past 70 years from tree height, DBH, canopy projection area, stem volume and aboveground biomass, which also considers tree parameters at the stem and crown levels.

With the improvement of forest inventories, the tree quantitative structure model (QSM) based on TLS point clouds has gradually emerged for tree model reconstruction, parameter acquisition and tree volume estimation [43-46], which makes it possible to estimate tree growth at the stem, crown and branch levels. QSM is a three-dimensional model that can describe the geometric and topologic structure of a tree, which can use a TLS point cloud to reconstruct the three-dimensional model of individual trees with high accuracy [47, 48]. Currently, there are many open-source
algorithms based on QSM that have been accurately applied to a variety of forests, such as PyBetree, Simpletree and TreeQSM [45, 47]. TreeQSM is regarded as one of the most accurate models for three-dimensional structure reconstruction, volume and biomass estimation [47, 49, 50] and has been used as the reference value to estimate the volume.

TreeQSM can directly acquire tree parameters, such as tree height, DBH, branch angle and volume of the stem and individual branches, and it has been widely used in tree volume estimation. This tool uses nonconnected features to segment the point clouds into stems and individual branches and fits the cylinders segmentally to build a quantitative structure model of a tree [47, 49]. To accurately and automatically estimate tree growth from different tree-level, this study proposes a strategy to estimate tree growth at the stem, crown and branch levels, combining QSM and TLS point cloud, e.g., tree height, DBH and stem volume at the stem level; crown diameter, canopy projection area and crown volume at the crown level; and volume of the first-order branch at the branch level. This study is to provide an example for tree growth studies considering the problem that the single tree-level parameter is difficult to describe the growth changes of trees throughout the whole growth period. This paper is organized as follows. Section 2 introduces the study area and data. Section 3 elaborates on the key steps of the proposed method. Section 4 introduces the performance of the proposed method and then evaluates the advancements, after discussions are presented and conclusions are drawn.

2. Study area and data

2.1 Study area

![Figure 1](image.png)

**Figure 1.** Study area. The green rectangle is the position of the larch forest in Weichang Manchu and Mongolian Autonomous County.
The study area is located in the Saihanba Mechanical Forest Farm (Figure 1), Weichang Manchu and Mongolian Autonomous County, Hebei Province, China. It is in a semiarid and semihumid continental monsoon climate and cold temperate zone, with long and cold winters, dry and windy springs, and hot and humid summers with strong sunlight. In this area, the annual average temperature is -1.5°C, and the annual precipitation is limited. The Saihanba Mechanical Forest Farm has the largest plantation in the world. The study area was selected in a larch forest, which is one of the main tree species in the region.

2.2 Data

In this study, a plot with size of 20 m×20 m in a 55-year-old larch plantation was selected (Figure 1), the forest density was approximately 400 trees/hectares, the average tree height was 20.55 m, the DBH was 29.49 cm, and the canopy closure was 0.42. The experiments were conducted in October 2018 and October 2020 in the deciduous period. A multiecho TLS (Rigel VZ1000) was used to acquire tree point cloud, whose maximum measurement range reached 1400 m and scanning accuracy reached 5 mm. Additionally, the vertical field of view was set to 30°~130°, the horizontal field of view was 0°~360°, and the resolution was 0.06°. The scan position was set at the center and four corners of the plot. Then, point clouds of year 2018 and 2020 were registered, denoised, and colored in green and red respectively, in which point clouds were registered by our previous works [51].

![Figure 2](image-url). Ground-based LiDAR data collected in 2018 and 2020. Yellow points are the point cloud collected in 2020, and blue points the point cloud collected in 2018.

In order to roughly assess the growth status of the larch in the study area (for example, whether it is close to maturity), we explored the growth period of larch in this study area by using the data from Hu [52] to complete the average annual growth curve and continuous annual growth curve of the stem volume in the Saihanba (Figure 3). The results showed that there was no intersection between the two curves, which meant that the 55-year-old larch was in the growth stage. The peak growth period of larch had passed, but it was still growing at a relatively high level.
3. Methods

Based on TLS data, this paper proposes to estimate tree growth at the stem, crown and branch levels. The tree height, DBH and stem volume were used to estimate tree growth at the stem level, crown diameter and volume at the crown level and first-order branch volume at the branch level. The proposed method mainly contains three steps: point cloud preprocessing, tree parameter estimation and tree growth analysis, as Figure 4 shows:

3.1 Point cloud preprocessing
Figure 5. Point cloud preprocessing: (a) is the registered point cloud, (b) is the point cloud after ground filtering (green points are vegetation points and red points are ground points), (c) is the individual tree points and (d) is the point cloud with the noise removed.

Point cloud preprocessing includes point cloud registration, ground filtering, individual tree detection, and denoising. Point cloud registration was performed using the fast point feature histogram method to achieve coarse alignment and fine registration and global adjustment based on the iterative closest point algorithm [51] (Figure 5a). The cloth simulation filtering algorithm [53] was used for ground point removal from the plot point clouds (Figure 5b). Individual tree detection was performed via manual segmentation to ensure the tree segmentation accuracy (Figure 5c). The separation algorithm [54] was used to segment the branch and leaf points and achieve twig point removal in the canopy. Noise points remained after wood-leaf separation and twig point removal, and we used connected-component labeling to remove the remaining noise point cloud (Figure 5d).

3.2 Tree parameter estimation

To acquire tree height from individual trees and DBH, stem volume was estimated using TreeQSM to estimate tree growth at the stem level; crown diameter, area and volume were estimated using the crown points of individual trees to estimate tree growth at the crown level; and the first-order branch volume was estimated using the TreeQSM to describe tree growth at branch level. The specific methods are as follows.

3.2.1 Tree height and crown diameter acquisition
Using individual trees, the vertical distance between the highest and lowest points was used as the tree height. Crown diameters were estimated based on individual crown points, we first detected the stems from the plots using the segment-based method from Zhang et al. [55] and then obtained the crown points from individual trees and their corresponding stem point clouds. The crown point cloud is projected vertically to the plane, and the average value of the crown diameter in the X and Y directions is used as the final crown diameter (CD), \( CD = (\Delta X + \Delta Y)/2 \); crown area is the projected area of the crown points on the XY plane, and the crown volume is obtained based on the alpha shapes algorithm which is based on qhull and Delaunay tetrahedralization of the individual crown points.

### 3.2.2 QSM verification and parameter estimation

During segmentation, TreeQSM uses multiscale voxels to replace individual points, which can improve the robustness of point cloud segmentation. First, uniformly sized voxels are used for coarse segmentation, and then multiscale voxels are used for detailed segmentation after coarse segmentation [56]. The two segmentation processes involve three parameters of voxel size, namely, patchdiam1, patchdiam2 max and patchdiam2 min, which can affect the size of the cylinders and then affect the results of tree 3D reconstruction [50]. Therefore, we completed the sensitivity analysis of the TreeQSM algorithm on the three individual parameters based on five reference trees, which were selected randomly from the larch plot, to obtain the optimal parameters. Since voxels are randomly generated, the QSMs of trees reconstructed from the same input parameters are not exactly the same. Therefore, the average of ten estimation results of individual trees is used as the final result. Figure 6 shows the reconstruction model of a single tree.
1) Reference data acquisition

We randomly selected five trees to manually obtain the reference values of the DBH, stem volume and first-order branch volume. DBH is the diameter at a height of 1.3 m from the lowest point of the stem, and the average diameters of the point cloud (10 cm-thick stem point cloud at 1.3 m) projected on XZ and YZ were used as the final DBH. Stem volume was obtained based on the stem curve using the diameter of the stem every 0.5 meters. Then, the stem volume was obtained based on the formula of the segmented cylinder (Equation (1)). The first-order branch volume acquisition is similar to the stem volume. The diameter of the branch is measured by each segmented cylinder segmented every 0.2 m to obtain the volume of the branch (Equation (2)).

\[
V_s = 0.5 \sum_{i=1}^{n} (S_1 + S_2) \times h
\]

\[
V_b = 0.5 \sum_{i=1}^{n} (S_1 + S_2) \times l
\]

Where \(V_s\) represents the volume of the stem, \(V_b\) is the volume of the first-order branch, and \(S_1\) and \(S_2\) are the upper and lower bottom sectional areas of the segmented cylinder, respectively (\(h\) is set as 0.5 m and \(l\) is set as 0.2 m in this study).

2) QSM verification and parameter estimation

We used the optimal input parameters to estimate the DBH, stem volume and first-order branch volume of the five reference trees based on TreeQSM individually. Then, compared with the parameters of five reference trees, the mean absolute deviation (MAD, Equation (3)) was used to describe the error of the estimation results of each tree. Finally, the DBH, stem volume and first-order branch volume of individuals in two periods were estimated, and the final DBH, stem volume and first-order branch volume were the averages of the results from ten reconstructions.

\[
MAD = \left| \frac{Q - R}{R} \right| \times 100\%
\]

where \(Q\) represents the parameter estimated by the QSM and \(R\) represents the reference.

3) Correction of first-order branch volume estimation

As mentioned earlier, TreeQSM has been used as a reference value to estimate the volume. However, its ability to estimate and correct the volume of individual branches has not been clarified. It is worth noting that the quality of the point cloud where the first-order branch grows from the stem leads to a certain deviation in the fitting of the first-order branches by TreeQSM, which accounts for approximately 1% to 5% of the first-order branches (Figure 7a). Reconstruct individual tree models ten times, then, the estimated volume of each first-order branch is considered abnormal if it reaches the rejection value (basal diameter > 0.1 m), according to the distribution of the basal diameters of the first-order branch (Figure 7b).
Figure 7. (a) Example of incorrect fitting of first-order collaterals (yellow rectangle), in which blue represents the stem, green is the first-order branch, and red is the secondary branch; (b) Distribution of the basal diameter of the first-order branches of the five reference trees. The basal diameters of the first-order branches are all within 0.1 meters and are mainly distributed within 0.08 meters.

3.3 Tree growth estimation

After the tree parameters were acquired, the absolute and average growth of each parameter were calculated. In addition, to estimate the growth rate of forest trees in two years, we calculated the growth rate of each tree parameter separately, which reflects the relative speed of tree growth in a certain period. The Pressler growth rate was used to estimate the growth rate. Taking the volume growth rate as an example,

\[
P = \frac{V_a - V_{a-n}}{V_a + V_{a-n}} \times \frac{200}{n}
\]  

where \(P\) is the growth rate of the stem volume, \(V_a\) is the final volume at the end of the study, \(V_{a-n}\) is the initial volume at the beginning of the study, and \(n\) is the study period (\(n=2, a=2020\)).

4. Results

4.1 Performance of TreeQSM

To verify the ability of TreeQSM to estimate the DBH, stem volume and the first order branch volume, we used mean absolute difference (MAD) to evaluate its accuracy. The results of tree parameters estimation accuracy of TreeQSM are shown in Table 1. The average MAD of the DBH, stem volume and the first order branch volume are 0.59%, 2.42%, and 7.29%, which indicated the TreeQSM algorithm can effectively acquire the DBH, stem volume and first-order branch volume of a single tree.

| Tree number | DBH | Stem volume | First order branch volume |
|-------------|-----|-------------|--------------------------|
| 1           | 1.10% | 6.53%       | 3.49%                    |
| 2           | 0.84% | 4.09%       | 8.50%                    |
| 3           | 0.39% | 4.28%       | 6.58%                    |
| 4           | 1.06% | 1.01%       | 3.73%                    |
5

|       | 1.91% | 1.52% | 3.94% |
|-------|-------|-------|-------|
| **avg** | 0.59% | 2.42% | 7.29% |

### 4.2 Evaluation of tree growth

The growth of each parameter of individual trees in the plot is shown in Table 2. The average growth of the tree height was 0.68 m, the average growth of the DBH was 0.65 cm, the average growth of the crown diameter was 0.25 m, and the average growth of the crown volume was 29.90 m³. The volume growth of the stem was 62.82 dm³, and the volume growth of the first-order branches was 49.48 dm³. Obviously, stem volume growth and first-order branching were equivalent, and they occupied a similar proportion in the growth of the whole tree volume. For the two-year absolute growth, the first-order branch and stem contribute the same amount; therefore, the first-order branches are a nonignorable part of the forest carbon sequestration capacity and productivity assessment.

Table 2. Statistics of the average growth of single trees in the plot

| Tree growth tree parameters | One-dimensional | Two-dimensional | Three-dimensional |
|-----------------------------|-----------------|-----------------|-------------------|
|                             | DBH/cm | H/m | CD/m | BCA/cm² | CA/m² | CV/m³ | SV/dm³ | FBV/dm³ |
| **absolute growth**         | 0.65    | 0.68 | 0.25 | 31.67   | 5.10   | 29.90 | 62.82  | 49.48   |
| **average growth**          | 0.33    | 0.34 | 0.13 | 15.84   | 2.55   | 14.95 | 31.41  | 24.74   |
| **growth rate**             | 1.10%   | 1.69%| 2.00%| 2.28%   | 10.83% | 6.04% | 5.28%  | 16.26%  |

**Notes:** DBH is the diameter at breast height, H is the tree height, CD is the crown diameter, BCA is the breast cross-sectional area, CA is the projected area of crown, CV is the crown volume, SV is the stem volume, FBV is the first-order branch volume.

In this study, we defined tree height, DBH and crown diameter as one-dimensional tree parameters, breast cross-sectional area and canopy projection area as two-dimensional parameters, and volume and biomass as three-dimensional parameters to analyze tree growth in different dimensions. The results showed that the 55-year-old larch in Saihanba was still growing at a relatively high level. In consideration of the growth changes in the different dimensions of forest growth, we used the DBH of each single tree to calculate the breast cross-sectional area to estimate tree growth at the two-dimensional level. One-dimensional parameters (e.g., tree height, crown diameter) and two-dimensional parameters (e.g., breast cross-sectional area) all had small changes in growth, and the growth rates were all within 3%; three-dimensional parameters (e.g., crown volume, stem volume and volume of first-order branch) showed large growth, and the growth rate was more than 5%. In addition, the absolute growth of first-order branch volume was equivalent to the stem volume, and its growth rate was the largest among all tree parameters. Compared to the stem level, the tree parameters at the crown level and the three-dimensional parameters more obviously described the growth of 55-year-old larch.

### 4.3 Tree growth verification

As mentioned in section 3.2, we used DBH, stem volume acquired by TreeQSM to estimate tree growth at the stem level and the first-order branch volume to describe tree growth at branch level.
To verify tree growth estimated from TreeQSM, we analyzed the accuracy of tree growth described by DBH and trunk volume (Table 3), in which the reference DBH is obtained by the least square fitting method, and the reference of stem volume is calculated based on the stem curve using the diameter of the stem every 0.5 meters based on the stem point cloud (Equation (1)). As show in Table 3, the MAD for DBH estimation of TreeQSM is 1.56%, and the MAD of stem volume estimation is 4.38%, which indicates TreeQSM can well estimate DBH and stem volume, and it can be used for tree growth estimation of DBH and stem volume.

| Table 3. Tree growth verification of TreeQSM |
|--------------------------------------------|
| Reference | TreeQSM | MAD  |
| DBH/cm    | 0.64    | 0.65 | 1.56% |
| SV/dm³    | 65.70   | 62.82 | 4.38% |

5. Discussion

Few researchers have considered the difference in the growth rate of trees at different tree levels, and due to the complexity of the canopy structure, few studies have considered tree growth in branches, we proposed estimating tree growth using tree parameters at the stem, crown and branch levels. Branches and their growth are an important part of the whole tree structure should not be ignored throughout the life of the tree.

5.1 Importance of tree growth at the branch level

In this study, we explored the proportion of the first-order branch in the whole tree quantitatively. The results showed that the volume of the first-order branches was almost 25% that of the stems (24.47% in 2018 and 29.75% in 2020), and the growth was 78.76% that of the stem, which was two times higher than the growth rate of the stem volume. Existing studies have also shown that branch biomass accounts for a large share of the whole tree and should be quantified and included in forest inventories [38]. Therefore, branches, especially first-order branches, are nonnegligible parts of tree growth, which should be considered in future tree growth studies.

5.2 Differences in the growth rate of individual trees and tree parameters

To analyze the difference in tree growth among individual trees in the plot, Figure 8 shows the growth rate of the individual tree parameters. The growth of tree height and DBH was not obvious, with growth rates within 5%; the growth of the breast cross-sectional area mainly reflected the increase in the DBH, and its growth rate was also small; and the growth rate of the crown diameter and stem volume was higher and reached approximately 5%. Crown volume variations between individual trees are similar to those of the first-order branch volume, and the growth rate is 5%~10%.

In general, the 55-year-old larch trees in the study area still have a high growth level. As the peak growth period has passed, the growth of one-dimensional and two-dimensional tree parameters, such as DBH, tree height and breast cross-sectional area, is not obvious. However, the growth of three-dimensional tree parameters, such as stem volume, crown volume, and first-order branch
volume, was more obvious. Therefore, a high growth level was observed for the 55-year-old larch in this study area, and the three-dimensional tree parameters (stem volume, first-order branch volume, and crown volume) could better reflect the growth of the 55-year-old larch. Compared with the parameters at the stem level, the crown of larch grew significantly in two years, meaning that the growth of the branches was significant.

Figure 8. Each parameter growth rate of individual trees. H: tree height; BA: breast cross-sectional area; SV: stem volume; CD: crown diameter; CV: crown volume; FBV: first-order branch volume

Figure 8 shows that the tree parameters at the crown and branch levels have significant differences among individual trees and show similar trends. The growth of the crown diameter is mainly due to length increases of the branch, and it may be affected by growth competition among the trees in the plot. Large differences in the growth of the crown diameter are observed among individual trees, which may also make the growth rate of the first-order branch volume vary greatly from 5% to 30%. Such hypotheses need further verification.

6. Conclusion

Because of the complexity of the crown structure, the growth of branches is rarely considered, and few studies have estimated tree growth at the branch level. Traditional tree growth is mainly estimated based on the increase in stem-level parameters, such as tree height, DBH, and stem volume. However, the parameters at a single level cannot describe tree growth over the whole growth period. In this study, we estimated tree growth at the stem, crown and branch levels to describe the growth of 55-year-old larch in Saihanba from 2018 to 2020. We acquired tree height, DBH and stem volume data at the stem level, crown diameter and volume data at the crown level, and first-order branch volume data at the branch level from individual trees. The results showed that over two years, the average growth of DBH was 0.65 cm, height was 0.68 m, crown diameter was 0.25 m, crown volume was 29.90 m³, stem volume was 62.82 dm³, and first-order branch volume was 49.48 dm³. For 55-year-old larch, the absolute growth in the first-order branch volume is close to that of the stem; that is, the first-order branch accounts for a considerable contribution to the forest productivity and carbon sequestration capacity increase. In addition, based on the visual structure of larch and analysis of the proportion of first-order branch and stem volume, this
paper concludes that first-order branch volume can account for approximately 25% of stem volume, which further illustrates the importance of quantifying branch volume and its growth in forest resource surveys. In addition, compared with one-dimensional parameters (tree height, DBH, and crown diameter), the three-dimensional tree parameters (crown, stem and first-order branch volume) can better describe tree growth for 55-year-old larch. Therefore, the estimation of tree growth should take the growth of tree parameters at different tree levels into account, especially at different forest ages.

In recent years, detailed QSM-based three-dimensional structure reconstruction algorithms have developed rapidly. Based on high-precision LiDAR data, this algorithm is expected to estimate the branch volume at all orders. Such work also contributes to research on the relationship between tree growth and environmental, climatic and other factors as well as the development of rational planting of artificial forests. Limited by the amount of data, this paper used only two phases of ground-based LiDAR point clouds to study the growth of larch. In the future, we can consider using multitemporal data of different tree species to study tree growth at different levels to explore tree growth trends and realize the nondestructive exploration of forest growth laws.

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**Data availability:** The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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