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

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Abstract:

Background: 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 (e.g., tree height, diameter at breast height (DBH), and crown diameter) obtained via forest in situ measurements, which are labor-intensive and time-consuming to perform and cannot easily describe the changes throughout the whole growth period of a tree. The combination of Terrestrial Laser Scanning (TLS) and Quantitative Structure Modelling (QSM) can accurately estimate tree structural parameters nondestructively and has the potential to estimate tree growth. Therefore, this paper estimates tree growth according to the stem-, crown-, and branch-level attributes observed by ground-based LiDAR point clouds. Compared with conventional methods, this paper used tree height, DBH, stem volume, crown diameter, crown volume and first-order branch volume to estimate the growth of 55-year-old larch trees in Saihanba at the stem, crown and branch levels, respectively.

Results: The experimental results showed that the absolute growth of the first-order branch volume was equivalent to that of the stems, which highlights the importance of branches in the study of tree growth. For 55-year-old larch, tree growth is mainly reflected in the growth of the crown, i.e., the growth of branches. Compared to one-dimensional parameters (tree height, DBH and crown diameter), the growth of three-dimensional parameters (crown, stem and first-order branch volumes) was more obvious.

Conclusions: For 55-year-old larch, three-dimensional tree parameters can more effectively describe tree growth, and the absolute growth of the first-order branch volume is close to the stem volume. In addition, it is necessary to estimate tree growth at different levels.

Keywords: tree growth, different levels, terrestrial laser scanning, QSM

1. Introduction

Forests play an important role in wood provisions, climate regulation, and water conservation (Zhao et al., 2018), and they act as a carbon sinks and account for approximately 50% of the global biosphere (Bowman et al., 2013). As one of the indicators of forest health, tree growth is closely related to the forest structure and global climate change (Dobbertin, 2005; Pretzsc, 2020; Coomes et al., 2007), and it 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 (Köhl et al., 2017; Maes et al., 2019; Forrester, 2019). Gregg et al. (2003) showed that the biomass of cottonwood is half of that in urban environments due to the higher ozone (O_3) in rural sites. Moreover, tree ring records can reflect the relationship between tree growth and the environment, is an important source of information on past temperatures for analyzing temperature changes at high latitudes (Wilmking et al., 2020). In addition, tree growth guides the planting of fast-growing trees, especially economic species. Thomas et al. (2020) showed that species interactions among fast-growing species will be more productive than those among the respective tree monocultures. For instance, a mixture of poplar and nitrogen-fixing herbaceous plants will be more productive. Therefore, accurately estimating tree growth can effectively improve the management of forest ecology, resources and plantations, and it is also the basis for analyzing tree growth correlations with genes, climate, environments and other factors.

Tree growth is defined as the increase of an individual tree in dimensions over time (Weiskittel et al., 2011; Bowman et al., 2013), and it is specifically quantified as the increase of tree parameters or its relative growth rate (Prodan, 1965). In addition, tree ring spacing changes over time (Mencuccini et al., 2005; Wilmking et al., 2020; Zhu et al., 2020), and changes in wood density (Briffa et al., 1998) are also used to reflect tree growth. However, tree ring acquisition and wood density sampling are destructive and labor intensive (Köhl et al., 2017; Pretzsch et al., 2018), and sampling in forests for annual ring records and wood density estimation makes it difficult to ensure sample representation (Bowman et al., 2013). In contrast, tree parameters are relatively easy to measure and commonly used to estimate tree growth. For example, tree height, stem volume and diameter at breast height (DBH) are used to estimate tree growth at the stem level, crown diameter and canopy projection area at the crown level, and volume and biomass at the tree level (Montoro Girona et al., 2017; Wu et al., 2020; Shoda et al., 2020; González-Díaz et al. 2020). However, research that has analyzed tree growth at multiple levels and used different parameters at different tree growth periods is lacking.

Tree height and DBH can describe tree growth radially and vertically (Liu et al., 2017), and the relationship between these measurements is commonly used to describe the tree growth model (Sumida et al., 2013). Because tree height and DBH are easy to measure, they are widely used to estimate tree growth, explore how genetic diversity affects tree growth, determine the effect of mixed planting on tree growth and analyze tree growth responses after thinning (González-Díaz et al., 2020; Thomas et al., 2020). Increases in tree height will tend towards zero as the tree approaches maturity (Bowman et al., 2013); thus, estimating tree growth via tree height alone is difficult to describe tree growth. In contrast, DBH and cross-sectional area continuously increase during the whole growth period (Bowman et al., 2013) and are also used in tree growth measurements (Shoda et al., 2020; Wu et al., 2020). However, the same increase in DBH has

varied impacts on the biomass in trees of different sizes, especially for trees with large crowns. Canopy area, volume and biomass have also been used to estimate tree growth in some studies (Brunner & Forrester, 2020; Chave et al., 2008; Hember et al., 2012; Zhao et al., 2018). Volume and biomass are difficult to acquire directly and thus are derived from tree height and DBH based on allometric equations (Cole & Ewel, 2006; Yuen et al., 2016). Tree height and DBH are the parameters at the stem level, and the canopy area is the parameter at the crown level. To describe tree growth in different components, tree height and crown diameter were used to estimate tree growth at the stem and crown levels (Montoro Girona et al., 2017), and tree height, DBH, canopy area, stem volume, aboveground biomass, and annual average growth were separately analyzed to estimate tree growth based on relevant research over the past 70 years (Pretzsch, 2020), which provided a reference for the estimation of tree growth at different levels.

Tree parameter acquisition relies on in situ measurements in forest sample plots; however, acquiring sufficient tree parameters is time-consuming and difficult (Liang et al., 2019), which is why tree growth is usually estimated using easy-to-measure parameters or existing forest inventory data (Wang et al., 2001; Zhang et al., 2020). In recent years, with the development of remote sensing technology, images and point clouds have been widely used in forest inventories (Shao et al., 2020a). Based on UAV and satellite images, forest canopy height (Persson et al., 2016) and biomass estimation (Maack et al., 2015; Jiang et al., 2019) can be nondestructively acquired and have promoted tree growth estimations at a large scale (Iizuka et al., 2020; Zhu et al., 2020). However, determining accurate tree growth at the individual tree level is difficult (Bowman et al., 2013), and other parameters, such as the DBH and crown diameter, are difficult to acquire. In contrast, as an active remote sensing method, LiDAR technology has high forest detection capabilities, can achieve tree and plot-level parameters with high accuracy (Pang et al., 2005; Liang et al., 2018; Liu et al., 2018), and has been widely used for tree parameter and biomass measurements (Srinivasan et al., 2015; Calders et al., 2015; Gonzalez de Tanago et al., 2018). Ground-based LiDAR technology has solved the problem of time-consuming, labor-intensive traditional in situ measurements in forests (Shao et al., 2020b) and can efficiently carry out repeated forest inventories, making it possible to estimate tree growth based on multitemporal ground-based LiDAR data (Srinivasan et al., 2014). Luoma et al. (2021) have showed the ability and possibilities of the TLS point cloud to characterize the stem form and volume allocations growth changes in two periods.

The crown structure of a tree is complex. Compared with the stem, it is more difficult to quantify the branch structure parameters. The study of forest biomass and carbon storage is mainly based on allometric equations at the tree and forest levels (Tackenberg, 2007; Fordjour et al., 2013), and few studies have focused on tree branches. As the main component of the crown, branches are indispensable elements of the tree structure. 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 $\frac{1}{3}$ of the carbon consumption in forest ecosystems; moreover, branch respiration accounts for approximately 50% of the total annual respiration of the forest (Damesin et al., 2002). In addition, branches account for a significant proportion of the total tree biomass estimation and should be quantified and included in future forest resource surveys (Hauglin et al., 2014). However, due to the complex structure, branches are difficult to directly measure, and the volume and biomass of branches are mostly acquired by regression models, which are fitted based on the branch length, branch basal diameter (Damesin et al., 2002) and

crown parameters (Hauglin et al., 2013; Hauglin et al., 2014) at the tree level based on in situ measurements in forest sample plots.

Tree growth processes can be reflected in root growth, bud growth, stem growth, branch growth and foliage growth (Dobbertin, 2005), and there are great differences in the growth rate of tree components at different growth periods (Bowman et al., 2013). Estimating tree growth at a single level cannot easily describe increases in all tree components. With the development of ground-based LiDAR high-precision tree parameter acquisition, QSM of trees based on TLS point clouds has gradually emerged, and this method has been widely used in tree model reconstruction, parameter acquisition and tree volume estimation (Du et al., 2019; Hackenberg et al., 2014; Putman et al. 2018; Raunonen et al., 2013; Stovall et al., 2017, 2018), which makes it possible to estimate tree growth at the stem, crown and branch levels. Therefore, to accurately and automatically estimate tree growth, this study proposes a strategy that combines tree attributes at different levels to estimate tree growth based on ground-based LiDAR point clouds, in which the structural attributes are estimated by individual tree point clouds and QSM. In addition, 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. 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. Section 5 presents a discussion and the conclusions.

2. Study area and data

2.1 Study area

The study area is located in the Saihanba Mechanical Forest Farm (Figure 1 (a)), Weichang Manchu and Mongolian Autonomous County, Hebei Province, China. It is located 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. Saihanba Mechanical Forest Farm has the largest plantation in the world. The sample forest plots of this study consisted of larch trees, which are one of the main tree species in the region.

Figure 1. Study area. The red rectangle is the position of the larch forest in Weichang Manchu and Mongolian Autonomous County.

2.2 Data

In this study, a $20\text{m} \times 20\text{m}$ plot in a 55-year-old larch plantation was selected (Figure 1), and the forest density was approximately 400 trees/hectares. The experiment took place in October 2018 and October 2020 in the deciduous period. A Rigel VZ1000 multiecho ground-based 3D laser scanner was used, and the maximum scanning distance can reach 1400 m and the scanning accuracy can reach 5 mm. During the data collection, the vertical field of view was set to $30^\circ \sim 130^\circ$, the horizontal field of view was $0^\circ \sim 360^\circ$, and the resolution was 0.06° . The scan position was set at the center and four corners of the plot. As shown in Figure 2, the point cloud was registered, denoised, and colored according to height.

Figure 2. Ground-based LiDAR data collected in 2018 and 2020

To explore the growth period of larch in this study area, we used the data from Hu (2018) to complete the average annual growth curve and continuous annual growth curve of the stem volume in the Saihanba (Figure 3). The results show that there is no intersection between the two curves, which means that the 55-year-old larch is in the growth stage. The peak growth period of larch has passed, but it is still growing at a relatively high level (Hu, 2018).

Figure 3. Average annual growth curve and continuous annual growth curve of stem volume in Saihanba over 60 years

3. Method

This paper estimates tree growth by combining tree parameters at different levels. These tree parameters are derived from ground-based LiDAR point clouds and include the tree height, DBH and stem volume, and they are 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. Tree height is measured from individual tree point clouds directly, crown-level parameters are estimated from individual crown point clouds, and the DBH, stem and branch volume are estimated by QSM (shown in Figure 4). The proposed method mainly contains three steps: point cloud preprocessing, tree parameter acquisition and tree growth estimation. The preprocessing of point clouds includes point cloud registration, denoising, ground filtering and individual tree segmentation. Then, the structural parameters of the segmented tree are estimated. Five trees are randomly selected as reference data and used to verify the structural parameters obtained from the QSM reconstruction model. Finally, the tree growth estimation is executed based on these tree parameters.

Figure 4. Main flow chart of this study on the growth of larch in Saihanba

3.1 Point cloud preprocessing

Point cloud preprocessing mainly includes the following 4 steps: point cloud registration, ground point filtering, individual tree detection and denoising. 1) Point cloud registration was performed using the fast point feature histogram (FPFH) method to achieve the coarse alignment and the fine registration and global adjustment based on ICP (iterative closest point) algorithm (Zhang et al., 2021) (Figure 5 A). 2). The cloth simulation filtering (CSF) algorithm (Zhang et al., 2016) was used for ground point removal from the plot point clouds. 3) Individual tree detection was performed via manual segmentation to ensure the tree segmentation accuracy (Figure 5 B). 4) The separation algorithm (Vicari et al., 2019) is used to segment the branch and leaf points and achieve twig point removal in the canopy (Figure 5 C). Noise points remained after wood-leaf separation and twig point removal, and then we used connected-component labeling (connected-component labeling, CCL) to remove the remaining noise point cloud (Figure 5 D).

Figure 5. Point cloud preprocessing

3.2 Tree parameter acquisition

To achieve tree growth estimation at the stem, crown and branch levels, tree height, crown diameter and crown volume were acquired based on the individual tree point cloud, and DBH, stem volume and first-order volume were estimated using the TreeQSM algorithm. The specific methods are as follows.

3.2.1 Tree height and crown diameter acquisition

After tree segmentation, we acquired tree height individually. The vertical distance between the highest and lowest points was used as the tree height. To acquire the crown parameters more accurately, we first detected the stems from the plots using the segment-based method from Zhang et al. (2019) 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), $CD = (\Delta X + \Delta Y) / 2$. The crown volume is obtained based on the alpha shapes algorithm in MATLAB, which is based on qhull and Delaunay tetrahedralization of the individual crown points (http://www.dylan-muir.com/articles/alpha_hulls/).

3.2.2 QSM verification and parameters estimation

A quantitative structure model (QSM) is a three-dimensional model of a tree that can describe the geometric and topologic structure of a tree. It uses the TLS point cloud to reconstruct the three-dimensional model of individual trees with high accuracy (Hackenberg et al., 2014; Stovall

et al., 2018). Currently, QSM is widely used to achieve fine three-dimensional structure reconstruction of a single tree (Hackenberg et al., 2014; Stovall et al., 2018; Fan et al., 2020), and there are many open source algorithms based on QSM that have been well applied to a variety of forests, such as Pypetree, Simpletree and TreeQSM (Delagrangé et al., 2014; Hackenberg et al., 2015; Raunonen et al., 2013). TreeQSM is regarded as one of the most accurate models for three-dimensional structure reconstruction, volume and biomass estimation (Delagrangé et al., 2014; Hackenberg et al., 2015; Brede et al., 2019; Moorthy et al., 2020) and has been used as the reference value to estimate the volume (Fan et al., 2020).

TreeQSM (<https://github.com/InverseTampere/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 and acquisition of aboveground biomass. 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 (Brede et al., 2019; Fan et al., 2020; Hackenberg et al., 2015). 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 (Fan et al., 2020; Kunz et al., 2017). The two segmentation processes involve 3 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 (Moorthy et al., 2020). Therefore, we completed the sensitivity analysis of the TreeQSM algorithm on the 3 individual parameters based on 5 reference trees to obtain the parameters that can obtain the best estimation results. Since voxels are randomly generated, the QSMs of trees reconstructed from the same input parameters are not exactly the same (Moorthy et al., 2020); therefore, the average of 10 estimation results of individual trees is used as the final result. In addition, Figure 6 shows the reconstruction model of a single tree.

Figure 6. QSM reconstruction, point cloud of a tree (left) and its corresponding 3D model (right) reconstructed by QSM

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. 1) DBH is the diameter at a height of 1.3 m from the lowest point of the stem, and we used the average diameters of the point cloud (10 cm-thick stem point cloud at 1.3 m) projected on the XZ and YZ as the final DBH. 2) Stem volume was obtained based on the stem curve using the diameter of the stem every 0.5 meters based on the stem point cloud. Then, the stem volume was obtained based on the formula of the segmented cylinder (formula (1)) (as shown in Figure 7). 3) 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 (formula (2)).

$$V_s = 0.5 \sum_{i=1}^n (S_1 + S_2) * h \quad (1)$$

$$V_b = 0.5 \sum_{i=1}^n (S_1 + S_2) * l \quad (2)$$

where V_s represents the volume of the trunk, 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. Here, $h = 0.5$ m and $l = 0.2$ m.

Figure 7. Method of acquiring the volume of the tree stem and branch

2) QSM verification and parameters estimation

Using the best input parameters, we estimated the DBH, stem volume and first-order branch volume of the 5 reference trees based on TreeQSM individually. Then, compared with the parameters of 5 reference trees, we use the mean absolute deviation (MAD, formula (3)) to describe the error of the estimation results of each tree. Finally, the DBH, stem volume and first-order branch volume of individuals in the two plots were estimated and the final DBH, stem volume and first-order branch volume were the averages of the results from 10 reconstructions.

$$MAD = \left| \frac{Q-R}{R} \right| * 100\% \quad (3)$$

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

3.3 Tree growth estimation

In this paper, tree growth is described as the increase in tree parameters from 2018 to 2020. Tree height, DBH and stem volume are used to estimate tree growth at the stem level; crown

diameter and crown volume are used to estimate tree growth at the crown level; and first-order branch volume is used to describe tree growth at the branch level. Before performing tree parameter acquisition from the point clouds, point cloud registration was implemented to find the individual trees corresponding to 2018 in the point cloud of 2020. We manually achieved coarse registration from the point cloud of 2020 to 2018 in the software CloudCompare (<https://www.danielgm.net/cc/>) and then used the ICP method to achieve fine registration.

After tree parameter acquisition, the absolute and average growth of each parameter was calculated. In addition, to estimate the growth rate of forest trees in two years, we calculated the growth rate of each tree parameter separately. This value 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, $P = \frac{V_a - V_{a-n}}{V_a + V_{a-n}} \times 200/n$, 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. Here, n=2 and a=2020.

4. Results

4.1 Performance of tree parameters estimated by QSM

As mentioned in section 3.2.2, we randomly selected 5 reference trees to verify the performance of the tree parameters estimated by TreeQSM. The results are shown in Table 1, Table 2 and Table 3. The average MAD of the DBH was 0.59%, the average MAD of the stem volume was 2.42%, and the first-order volume was approximately 7.29%. Therefore, the TreeQSM algorithm can effectively acquire the DBH, trunk volume and first-order branch volume of a single tree.

Table 1. DBH (cm) verification

Tree number	Reference	QSM	MAD
2	26.36	26.65	1.10%
3	28.55	28.31	0.84%
8	28.18	28.07	0.39%
9	27.29	27.58	1.06%
13	33.91	34.56	1.91%
avg	28.86	29.03	0.59%

Table 2. Stem volume (dm³) verification

Tree number	Reference	QSM	MAD
2	570.74	533.46	6.53%
3	629.20	603.49	4.09%
8	486.89	466.04	4.28%
9	634.71	628.30	1.01%
13	869.09	882.28	1.52%
avg	638.13	622.71	2.42%

Table 3. First-order branch volume (dm^3) verification

Tree number	Reference	QSM	MAD
2	87.58	90.64	3.49%
3	104.36	113.23	8.50%
8	146.17	155.79	6.58%
9	181.45	188.21	3.73%
13	244.92	254.58	3.94%
avg	152.90	164.04	7.29%

As mentioned in section 3.2.2, TreeQSM is regarded as one of the most accurate models for three-dimensional structure reconstruction, volume and biomass estimation and has been used as the 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 will lead to a certain deviation in the fitting of the first-order branches by TreeQSM, and it accounts for approximately 1% to 5% of the first-order branches (as shown in Figure 8(b)). According to the basal diameter distribution of the first-order branch of the 5 reference trees (as shown in Figure 8(a)), after using TreeQSM to reconstruct the single tree model 10 times, the estimated volume of each first-order branch is abnormal if it reaches the rejection value (basal diameter > 0.1 m).

Figure 8. (a) Distribution of the basal diameter of the first-order branches of the 5 reference trees. The basal diameters of the first-order branches are all within 0.1 meters and are mainly distributed within 0.08 meters. (b) Example of incorrect fitting of first-order collaterals. In this figure, blue represents the stem, green is the first-order branch, and red is the secondary branch.

Inside the yellow rectangle is the first-order branch which is incorrectly reconstructed.

4.2 Evaluation of tree growth

The growth of each parameter of individual trees in the plot is shown in Table 4. The average growth of the tree height is 0.68 m, the average growth of the DBH is 0.65 cm, the average growth of the crown diameter is 0.25 m, and the average growth of the crown volume is 29.90 m^3 . The volume growth of the stem is 62.82 dm^3 , and the volume growth of the first-order branches is

49.48 dm^3 . Obviously, stem volume growth and first-order branch 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 4. Statistics of the average growth of single trees in the plot

Tree growth	One-dimensional			Two-dimensional		Three-dimensional		
tree parameters	DBH/cm	H/m	CD/m	BCA / cm^2	CA/ m^2	CV/ m^3	SV/ dm^3	FBV/ dm^3
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 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

From the results, the 55-year-old larch in Saihanba is still at a relatively high growth level. Considering 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 have small changes in growth, and the growth rates are all within 3%; three-dimensional parameters (e.g., crown volume, stem volume and volume of first-order branch) show large growth, and the growth rate is more than 5%. In addition, the absolute growth of first-order branch volume is equivalent to the stem volume, and its growth rate is the largest among all tree parameters. Compared to stem level, the tree parameters at the crown level and the three-dimensional parameters are more obvious in describing the growth of 55-year-old larch.

5. Discussion

Due to the complexity of crown structure, existing studies mostly use DBH, tree height and stem volume to estimate tree growth at the stem level or use existing forest survey data to estimate tree growth. Some researchers have added parameters such as crown diameter to study tree growth at the crown level and biomass at the tree level. However, few studies have used different tree parameters to estimate tree growth at different levels, especially growth at the branch level. However, the parameters at a single level cannot easily describe tree growth over the whole growth period. Therefore, it is important to select different parameters to estimate tree growth in different periods.

5.1 Importance of tree growth at the branch level

Compared with stems, the lower economic value of branches makes them less concerned in forestry production. However, branches play an important role in the whole tree structure. They

are the main constituent of the canopy structure and the transmitter of photosynthesis products of leaves. In addition, they play an important role in the carbon balance of forest ecosystems. Therefore, we explored the proportion of the first-order branch visually and quantitatively.

As shown in Figure 9, because of the lower proportion of secondary branches, the first-order branches accounted for a significant proportion of the whole tree, accounting for 25% of the trunk volume (Table 5). From Table 6, the volume growth of the first-order branches is approximately 49.48 dm^3 , while that of the stems is 62.82 dm^3 , which accounts for approximately 78.76% of the growth of the trunk volume. In addition, the first-order branch is even two times higher than the growth rate of stem volume. Therefore, the branch, especially the first-order branch, is a nonnegligible part of tree growth. Existing studies have shown that branch biomass accounts for a large share of the whole tree and should be quantified and included in future forest inventories (Hauglin et al., 2014). Therefore, branch growth should also be added in future tree growth studies.

Figure 9. Visual of the larch structure

Table 5. Proportion of first-order branch volume

	Year 2018	Year 2020
$\frac{V_{first-order\ branch}}{V_{stem}}$	24.47%	29.75%

Table 6. Proportion of tree growth at first-order branches

	Tree growth	Growth rate
$\frac{P_{first-order\ branch}}{P_{stem}}$	78.76%	307.95%

5.2 Main parameters to quantify the growth of 55-year-old larch

To understand tree growth visually, we mapped it with a point cloud as shown in Figure 10. The point cloud was preprocessed after denoising, ground filtering, and underground vegetation removal. The color represents the point distance between 2020 and 2018; that is, the farther the distance is, the more obvious the growth, and the color changes from blue to red. Figure 10 shows that the stem is blue, e.g., the stem growth is not obvious, while the outer layer of the canopy is green, which can clearly reflect the increase of the crown, e.g., the growth in length of the branches. Therefore, tree growth was mainly reflected in the crown for 55-year-old larch from 2018 to 2020, which is consistent with the conclusion of Table 4. In addition, the closer to the top of the canopy, the more obvious the tree growth, which may be the reason for the increasing branch length and number of twigs.

Figure 10. Visual growth of 55-year-old larch from 2018 to 2020

5.3 Difference in the growth rate of individual trees and tree parameters

To analyze the growth difference among individual trees in the larch plot, Figure 11 shows the growth rate of the individual tree parameters. The growth of tree height and DBH is not obvious, with growth rates within 5%; the growth of the breast cross-sectional area mainly reflects the increase of the DBH, and its growth rate is also very small; and the growth rate of the crown diameter and stem volume is higher and reached approximately 5%. Crown volume variations between individual trees are similar to that 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 relatively 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 branches was significant.

Figure 11. Each parameter growth rate of individual trees in the plot. H: tree height; BA: breast cross-sectional area; SV: stem volume; CD: crown diameter; CV: crown volume; FBV: first-order branch volume

Figure 11 shows that the tree parameters at the crown and branch levels have great 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. Great differences in the growth of the crown diameter are observed among individual trees, which also may make the growth rate of the first-order branch volume vary greatly from 5% to 30%. Such hypotheses need further verification

6. Conclusions

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 easily 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 the over two years average growth of DBH was 0.65 cm, height was 0.68 m, crown diameter was 0.25 m, crown volume was 29.90 m^3 , stem volume was 62.82 dm^3 , and first-order branch volume was 49.48 dm^3 . For 55-year-old larch, the absolute growth of the first-order branch volume is close to the stem volume; that is, the first-order branch accounts for a considerable contribution towards increasing the forest productivity and carbon sequestration capacity. In addition, based on the visual structure of larch and an analysis of the proportion of first-order branches and stem volume, this paper concludes that the first-order branch volume accounts for approximately 25% of the trunk volume, which provides certain evidence for quantifying branches and including it in future 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.

Considering the importance of branches in forest resource surveys and variations in the growth of different tree parameters in different periods, this paper proposes that tree growth should be estimated at the stem, crown, and branch levels. The results and conclusions of this paper emphasize the importance of branch growth in the study of tree growth and provide an example of a nondestructive study of tree growth in Saihanba. In recent years, detailed QSM-based three-dimensional structure reconstruction algorithms have developed rapidly. Based on high-precision LiDAR data acquisition, 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 only used 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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