



Evaluating tree branch angle measurements of European beech using terrestrial laser scanning

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ABSTRACT

Branch angles are an important plant morphological trait affecting light interception within forest canopies. However, studies on branch angles have been limited due to the time-consuming nature of manual measurements using a protractor. Terrestrial laser scanning (TLS), however, provides new opportunities to measure branch angles more efficiently. Despite this potential, studies validating branch angle measurements from TLS have been limited. Here, our aim is to evaluate both manual and automatic branch angle measurements of European beech from TLS data using traditional field-measurements with a protractor as a reference. We evaluated the accuracy of branch angle measurements based on four automated algorithms (aRchiQSM, TreeQSM, Laplacian, Semantic-Laplacian) from TLS data. Additionally, we assessed different ways of manual branch angle measurements in the field. Our study was based on a dataset comprising 124 branch angles measured from six European beech in a European deciduous forest. Our results show that manual branch angle measurements from TLS data are in high agreement with the reference (root-mean-squared error, RMSE: $[3.57^{\circ}-4.18^{\circ}]$, concordance correlation coefficient, CCC: $[0.95-0.97]$) across different branch length positions. Automated algorithms also are in high agreement with the reference although RMSE is approximately twice as large compared to manual branch angle measurements from TLS (RMSE: $[9.29^{\circ}-10.55^{\circ}]$, CCC: $[0.83-0.86]$) with manual leaf points removal. When applying the automatic wood-leaf separation algorithm, the performance of the four methods declined significantly, with only approximately 20 branch angles successfully identified. Moreover, it is important to note that there is no influence of the measurement position (branch surface versus center) for branch angle measurements. However, for curved branches, the selection of branch measurement length significantly impacts the branch angle measurement. This study provides a comprehensive understanding of branch angle measurements in forests. We show that automated measurement methods based on TLS data of branch angles are a valuable tool to quantify branch angles at larger scales.

1. Introduction

Tree architecture is the structure and form of a tree, including features such as crown shape, branching structure, stem shape, and leaf arrangement (Su et al., 2023). Tree structural traits play an important role in quantifying a tree's competitiveness for light, nutrients and water (Beland et al., 2019; Eloy et al., 2017; MacFarlane and Kane, 2017; Pitkänen et al., 2022). Among these traits, the branch angle, defined as the angle between adjacent branches, and branch angle distribution emerges as a crucial structural trait influencing light interception and distribution within the forest canopies (Cushman and Machado, 2020; Yang et al., 2019). Branch angle distribution has been shown to correlate with a tree's maximum effective leaf area and photosynthetic efficiency,

since branching traits can significantly influence light interception within the canopy (Honda and Fisher, 1978; Yang et al., 2019). Yang et al. (2019) demonstrated that in high density plantations, leaf photosynthetic performance varies with branch angle. Trees can adjust branch angles to optimize effective leaf area, a process that involves a trade-off between branch angle and branch length (Kempf and Pickett, 1981; Pickett and Kempf, 1980; Viridi et al., 2023). Evidence from various studies suggests that this mechanism is observed in trees at different successional stages and with diverse growth habits (Kempf and Pickett, 1981; Pickett and Kempf, 1980). Specifically, shrubs in later successional stages tend to have longer branches and larger branch angles compared to those in earlier stages, reducing leaf overlap (Kempf and Pickett, 1981). Extensive branch angle quantification is thus important for

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gaining insights into the mechanisms employed by trees to optimize light interception.

Typically, branch angles are measured by fixing one side of the protractor on the main branch of a pair of branches, and then twisting the other side of the protractor onto a lower order branch (Kint et al., 2010; Lintunen and Kaitaniemi, 2010). However, manual branch angle measurements using a protractor are very time-consuming, especially for large trees. There can be many curved branches and branches that surpass the length of the protractor, and several operations are required to fix the protractor perfectly on the branch. In order to reduce measurement errors, three measurements are usually required for each branch. Measuring branch angles often requires the use of ladders or tree climbing, which further increases measurement time. Moreover, manual measurements using a protractor can only capture a subset of the available branch angles. These limitations impede the advancement of studies on branch angles.

Terrestrial laser scanning (TLS) is a promising technique to measure branch angles. TLS, an active remote sensing technology, enables the capture of detailed 3D information of trees in the form of point clouds (Calders et al., 2020; Disney, 2019; Liang et al., 2016). Based on TLS point cloud data, a variety of tree structural traits, including tree height, diameter at breast height, and crown volume can be measured with high accuracy (Balestra et al., 2024; Liang et al., 2016; Panagiotidis et al., 2022; Terryn et al., 2022). However, the quality of TLS data is subject to factors such as radiation principles, scanner characteristics, weather conditions, and the complexity of the forest environment. For instance, considering the RIEGL VZ-400i with a beam divergence of 0.35 mrad and an exit beam diameter of 7 mm, the spot diameter at a distance of 25 m is estimated to be 16.75 mm (Demol et al., 2022). Target branches are typically surrounded by neighboring leaves and branches, leading to the incorporation of information from both the target and its surroundings, thus generating mixed pixels within the spot (Schmitz et al., 2020). Consequently, the point cloud data resolved from these spots may contain inherent errors, which are further exacerbated by occlusion effects. Two studies (Demol et al., 2022; Morhart et al., 2024) indicated this error in point cloud data causes inaccurate modeling of small branches. These considerations have raised the necessity of validating manually measured branch angles from forest TLS data. Precise manual branch angle measurements on TLS data are important for further developing automated algorithms to retrieve branch angles using TLS data, as it can provide a wide variety of reliable validation data and training data for branch angles.

The rapid development of automated algorithms has enabled us to quickly extract branch angles from TLS data (Li et al., 2020; Wu et al., 2021). The general approach for automatically extracting branch angles involves deriving the skeleton from individual point clouds and subsequently adding topological information to the skeleton. Although various algorithms have been developed to obtain skeletons from point cloud data, many of these algorithms have primarily originated from the field of computer graphics (Bucksch and Lindenbergh, 2008; Cao et al., 2010; Middleton et al., 2022; Zhang et al., 2021). Some of these algorithms can be used to process individual tree point clouds. The Laplacian algorithm (Cao et al., 2010) has exhibited good performance in the skeletonization of individual point clouds. Two recent studies (Li et al., 2020; Wu et al., 2021) have automatically extracted branch angles using the Laplacian algorithm from TLS data. However, the performance of this algorithm is not satisfactory when confronted with substantial variations in size among adjacent branches (Meyer et al., 2023). To address this challenge, a semantic Laplacian algorithm has emerged, facilitating weighted skeletonization for branches of differing sizes (Meyer et al., 2023). Furthermore, quantitative structure models (QSMs) have demonstrated effectiveness in not only extracting tree traits but also deriving skeletons, which is recognized as a crucial tool for various forest traits (Åkerblom and Kaitaniemi, 2021; Raunonen et al., 2013; Wilkes et al., 2021). QSMs are cylinder models reconstructed from 3D point cloud data that contain spatial coordinates, geometry and topological information. Lau et al.

(2019) destructively collected branches larger than 10 cm and found that QSM can accurately reconstruct the length and volume of these branches. A recent validation study (Morhart et al., 2024) on smaller branches revealed that the branch volume extracted by QSM is less accurate, and the scanning distance significantly affects the measured length and volume of branches. However, due to the lack of manual branch angle measurements data in the field, the validation for branch angle is still lacking.

Here, our aim is to evaluate different methods to measure branch angles of European beech from tree point clouds. Specifically, we first assess different ways of manual branch angle measurements in the field. Secondly, we validate the reliability of manual branch angle measurements on TLS data at different branch lengths positions using manual measurement with a protractor as the reference. Finally, we evaluate the accuracy of four automated algorithms (aRchiQSM, TreeQSM, Laplacian, Semantic-Laplacian) to automatically extract branch angles from forest TLS data.

2. Materials and methods

2.1. Study area

The study area was situated in the Aelmoeseneiebos, a forest managed by Ghent University, Belgium (50°58'31.0" N, 3°48'17.1" E) (Blondeel et al., 2020). The research area of the forest is a mixed coniferous and broad-leaved forest and the main species include oak (*Quercus robur*), Norway spruce (*Picea abies*) and European beech (*Fagus sylvatica*), Sycamore maple (*Acer pseudoplatanus*), and European ash (*Fraxinus excelsior*). We selected six European beech trees of varying sizes, one of the most common species in European forests. Each tree had at least 3 s-order branches that could be measured with a 2-m ladder. Detailed information about the trees is provided in Table 1.

2.2. Terrestrial laser scanning

TLS data were collected using a RIEGL VZ-400i (RIEGL Laser Measurement Systems GmbH) scanner under nearly no-wind conditions at 300 kHz pulse repetition rate and 0.04° angular resolution. The instrument has a wavelength of 1,550 nm and a nominal beam divergence of 0.35 mrad. The azimuth and zenith range are 0°–360° and 30°–130° respectively. Five trees were scanned in leaf-on conditions and one tree was scanned in leaf-off conditions (Fig. 1), with the scanning locations situated 3–5 m from each tree, in August 2023. To scan the target branches as thoroughly as possible, we designed different scanning schemes for these six trees based on the spatial location of the target branches in the crown. Specifically, for the second-order branches that need to be scanned, at least two scans were performed to ensure their complete coverage. Please note that our objective is not to obtain the 3D structural information of the entire tree, and we did not use a standard scanning scheme (Wilkes et al., 2017). Among these trees, two trees used three sampling locations with two scans; one tree used five sampling locations with vertical scan; and the remaining three trees were close together and scanned at seven sampling locations with vertical scan (Fig. 1).

Point cloud data was co-registered in RiSCAN PRO (version 2.5.1;

Table 1
Summary of the height, diameter at breast height (DBH) for six scanned *Fagus sylvatica*.

Tree ID	DBH (m)	Tree height (m)
1	0.10	11.60
2	0.08	9.07
3	0.05	4.66
4	0.15	14.97
5	0.21	16.45
6	0.13	9.35

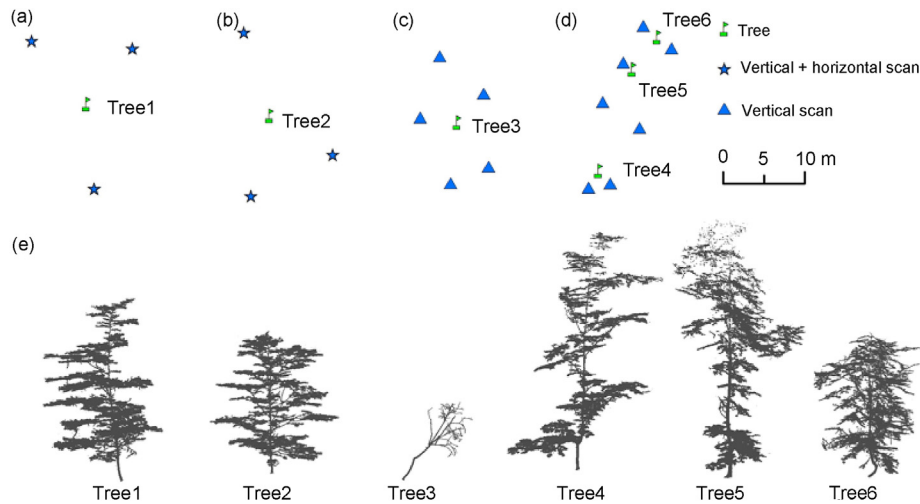


Fig. 1. Sampling pattern configurations for capturing TLS data and point cloud of 6 scanned trees. (a), (b) The two trees used three scan locations. (c) The tree used five scan locations and only scanned vertically. (d) The three trees were scanned at seven locations, and only vertical scan data was acquired at each location. (e) Point cloud data of individual trees.

RIEGL Laser Measurement Systems GmbH). And then, we filtered out the points from the point cloud with reflectance values less than -25 dB and greater than 5 dB, as well as those with pulse shape deviation greater than 15 (Calders et al., 2017). We manually segmented the six trees and manually removed the leaves for five leaf-on trees. To evaluate the performance of automatic branch angle extraction in leaf-on conditions, we applied the GBSeparation (Tian and Li, 2022) algorithm to automatically separate wood and leaf points clouds. Only the wood point clouds were used for assessing the accuracy of branch angle extraction.

2.3. Manual branch angle measurements

2.3.1. Branch angle definition from different branch positions

Manual branch angle measurements in the field involve defining three measurement points on two adjacent branches. However, there is high variability in the selection of measurement points across different studies (Ding et al., 2022; Hein and Splecker, 2007; Kint et al., 2010; Lintunen and Kaitaniemi, 2010). Here, to compare the differences in branch angles obtained from different measurement points, we define several measurement points according to the branch measurement position and the branch measurement length.

(1) Definition of branch angle measurement position on the main branch

First we determine the measurement position on the main branch. We divide the measurement position of the branch into the branch surface and branch center. To determine the branch center, we first identified the centerline of the main branch. Next, the centerline of the straight portion of the lower order branch was identified. The intersection of these two centerlines is the branch center point. The detailed position is shown in Fig. 2a.

(2) Determination of branch measurement length

After determining the measurement position on the main branch, the final measurement point can be determined by selecting different branch lengths on the lower order branch. Five branch measurement lengths are selected at the branch tangent, 25%, 50%, 75%, and 100% of the branch length. Eventually, we measure five branch angles at branch center based on five branch measurement lengths (Fig. 2c), and five branch angles at branch surface based on five measurement lengths (Fig. 2d).

We calculate the branch curvature defined as the angle measured at

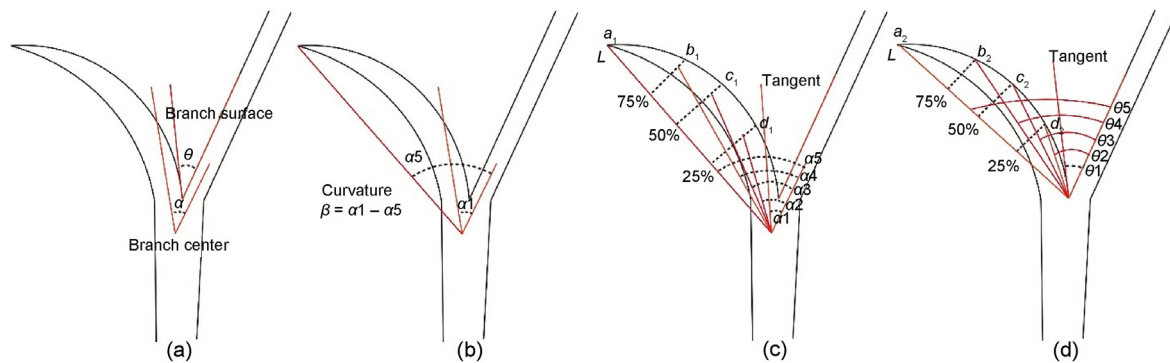


Fig. 2. Schematic diagram of tree angle definition. (a) is the measurement of the branch angle at different branch positions (branch center and branch surface); (b) is the calculation of the branch curvature; (c) and (d) are the measurement of the branch angle using different branch lengths (tangent, 25%, 50%, 75%, 100%) at branch center and branch surface, respectively. α is the branch angle measured at branch center; θ is the branch angle measured at branch surface; β is the branch curvature; $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ and α_5 are the branch angle measured at the branch tangent, 25%, 50%, 75%, 100% of the branch length at the branch center, respectively; $\theta_1, \theta_2, \theta_3, \theta_4$ and θ_5 are the branch angle measured at the branch tangent, 25%, 50%, 75%, 100% of the branch length at the branch surface, respectively; a_1, b_1, c_1, d_1 are the measurement positions at 100%, 75%, 50%, 25% branch lengths at branch center, respectively; a_2, b_2, c_2, d_2 are the measurement positions at 100%, 75%, 50%, 25% branch lengths at branch surface, respectively. L is the straight-line distance of the branches.

branch tangent minus angle measured at 100% branch length position (Fig. 2b). Note that branch curvature is calculated from manual field measurements of branch angles.

2.3.2. Manual branch angle measurements in the field

For the six trees in the study, all accessible surface and center branch angles (Fig. 2) of second-order branches, third-order branches and fourth-order branches were measured using a protractor (Winkeltronic 600, precision $\pm 0.1^\circ$). The availability of branch angles was determined by the highest position that could be reached using a 2-m-high ladder. We assigned the trunk as the first-order branch, the branches generated from the trunk as the second-order branch, and so on. Branch angles were measured only for branches with a main branch length longer than 5 cm. Among the branches that we measured, numerous exhibited a curved morphology. Additionally, certain branches surpassed the length of the measuring instrument. Consequently, aligning the sides of the Winkeltronic 600 with the measurement points on the branches proved challenging. To mitigate measurement uncertainty, these branches were measured three times, with the average value taken as the final branch angle. Finally, we collected 137 field-measured branch angles in total.

2.3.3. Manual branch angle measurements on TLS data

The complexity of a tree's branch structure poses challenges in identifying corresponding branches within point clouds with matching manually measured branches in the field. To address this, reflective circles (5-cm diameter) were employed during manual branch angle measurements in the field to mark corresponding branches. Subsequently, utilizing point cloud visualization based on reflectance values, we identified manually measured branches in the field from the point cloud. This approach facilitated accurate matching of branch point clouds to manual branch angle measurements in the field (Fig. 3). In dense forests, TLS does not always sample all branches of a tree and occlusion occurs. Occlusion in TLS measurements mostly occurs towards the top of the canopy as well as in the middle of tree crowns (Béland et al., 2014; Schneider et al., 2019). Although we used multiple scanning locations to mitigate occlusion, some branches were obscured by leaves, leading to 13 unobserved branches. Ultimately, point cloud data for 124 matched branches

were successfully obtained. Following the matching process, we manually measured five branch angles at five branch length positions for each branch, referencing the branch center (Fig. 1), using CloudCompare v2.13 (<https://www.danielgm.net/cc/>). The function of manually measuring branch angles from point cloud data has been included in CloudCompare. In this software, a branch angle is calculated by selecting three measurement points from the tree point cloud. To ensure accuracy, the selected points were validated by rotating 360° after the manual selection of three points.

2.4. Automatic extraction of branch angles

In the study, we used four algorithms (Laplacian algorithm, Semantic Laplacian, aRchiQSM, TreeQSM) to evaluate the accuracy of branch angle automated extraction from 3D point clouds. Here we briefly describe the implementation process of these four algorithms.

2.4.1. Extraction of branch skeleton point

2.4.1.1. aRchiQSM. We employed the aRchiQSM for point cloud skeleton extraction, involving four sequential steps (Fig. 4a). Firstly, the point cloud is divided into layers of regular thickness. Subsequently, the layers are divided into clusters based on point distance, where two points exceeding a specified distance are regarded as belonging to distinct objects. The centers of these clusters are then utilized as nodes of the skeleton, and through iterative processes, the skeleton is progressively constructed. Finally, a foundational tree topology is established by computing the daughter-parent relationships among each node. The algorithm was carried out using the aRchiQSM software (version 2.1.3, <https://github.com/umr-amap/aRchi/>). aRchiQSM does not provide a method for selecting optimal parameters. Therefore, we determined the final parameters through visual inspection of the QSM. The aRchiQSM (Martin-Ducup et al., 2020) relies on three key parameters that influence the accuracy of the tree reconstruction: D , cl_dist , and max_d . The parameter D determines cylinder size and the precision of bifurcation detection. The cl_dist parameter controls the re-segmentation of each cylinder, where overly small values can lead to erroneous subdivision,

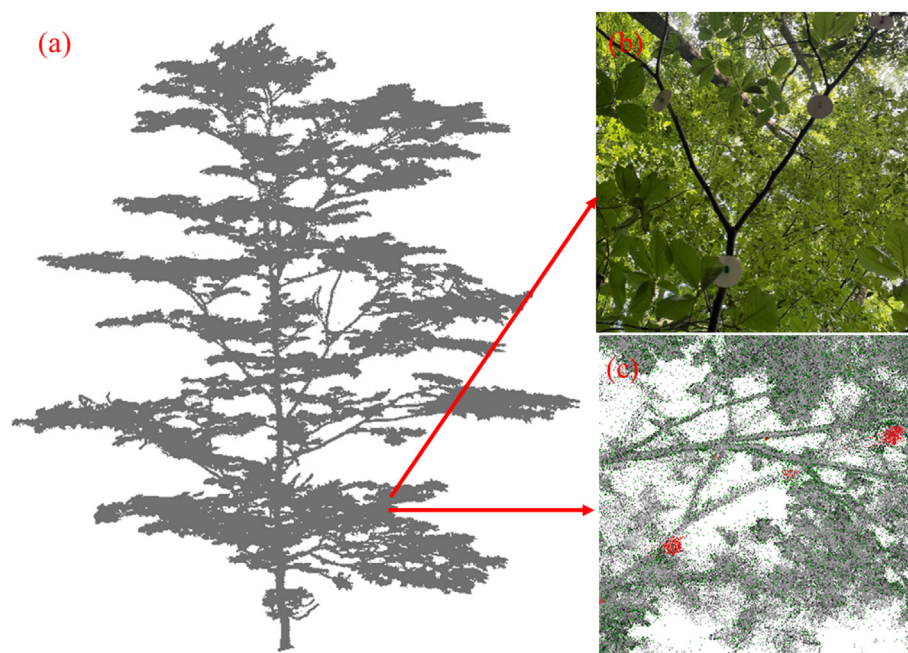


Fig. 3. Example of reflective circles in the field and point cloud. (a) Point cloud data of tree2. (b) Branches where angles need to be manually measured in the field, with white circles representing reflective markers. (c) Branches where angles are measured in the point cloud, with red points indicating reflective markers with high reflection values. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

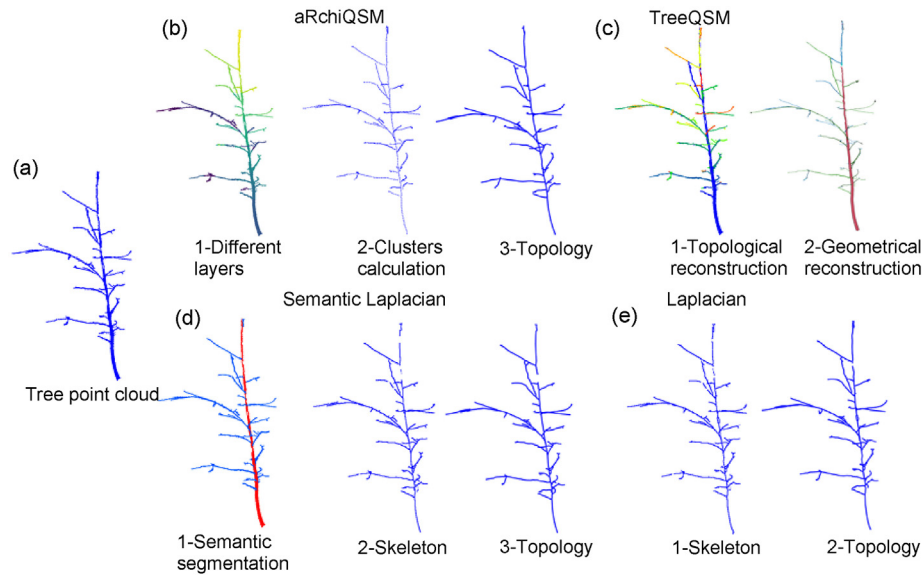


Fig. 4. A workflow explanation of different methods and final modeling results from tree1. (a) Wood point cloud data of tree1 after manually removed leaves. (b), (c), (d) and (e) are aRchiQSM, TreeQSM, Semantic Laplacian and Laplacian respectively.

while large values may fail to identify bifurcations accurately. The max_d parameter affects cylinder connectivity. Since aRchiQSM does not offer a method for optimal parameter selection, we adopt an automatic approach of aRchiQSM for cl_dist . max_d and initial D is set to 0.05 and 0.01, respectively. D is then incrementally increased by 0.01 until the optimal model is determined through visual inspection.

2.4.1.2. TreeQSM. TreeQSM was developed to efficiently apply cylinder models to TLS point clouds, considering the inherent structure of trees such as connectivity, branching, and branch tapering (Calders et al., 2015; Raunonen et al., 2013). Specifically, TreeQSM modeling consists of two primary steps (Fig. 4b). The initial step involves the topological reconstruction of the branching structure, which entails segmenting the point cloud into the stem and individual branches. The subsequent step focuses on the geometric reconstruction of branch surfaces through the least squares fitting of cylinders. The parameter combination was automatically defined using the latest version of TreeQSM (version 2.4.1, <https://github.com/InverseTampere/TreeQSM>). For the parameter combination, TreeQSM was run 10 times. The mean QSM to point cloud distance was computed for each QSM. The QSM with the smallest mean distance was identified as the best QSM and was selected for each tree.

2.4.1.3. Laplacian. Standard Laplacian-based contraction (LBC) (Cao et al., 2010) was used to contract the tree point clouds by solving the linear system of equations (Fig. 4c).

$$\begin{bmatrix} W_L L \\ W_H \end{bmatrix} P' = \begin{bmatrix} 0 \\ W_H P \end{bmatrix} \quad (1)$$

P is the 3D input point cloud; contracted point cloud P' ; W_L and W_H are sparse diagonal weighting matrices to regulate the contraction and attraction constraints respectively; L is defined as cotangent Laplacian matrix. By repeatedly solving the linear system of equations, the weight matrices W_L and W_H are updated, and L is recalculated.

2.4.1.4. Semantic Laplacian. Standard LBC is prone to mal-contraction in cases where there is a significant disparity in diameter between trunk and branches (Meyer et al., 2023). In order to address these topological artifacts, we used Semantic Laplacian-based contraction (S-LBC) (Fig. 4d). It first needs to divide the point cloud into trunk P_T and branch P_B parts. Then define a semantic matrix to weight the trunk point cloud and

branch point cloud differently.

$$\begin{bmatrix} S \circ W_L L \\ W_H \end{bmatrix} P' = \begin{bmatrix} 0 \\ W_H P \end{bmatrix} \quad (2)$$

S is the semantic weighting matrix; $\circ$ represents the Hadamard product and is a binary operation that takes in two matrices of the same dimensions and returns a matrix of the same dimensions.

2.4.2. Skeleton topology

The calculation of branch angles from skeleton data necessitates topological information at each branch bifurcation. In the case of aRchiQSM and TreeQSM, the topology is established through the daughter-parent relationship between each cylinder, and this information can be extracted directly from QSMs outputs. For LBC and S-LBC, the topological relationship of the branch skeleton is derived from the local approximation connectivity of raw point clouds based on a k -nearest neighbor graph (Cao et al., 2010; Meyer et al., 2023). This approach provides a means to infer the structural connectivity of branches within the point cloud, facilitating the subsequent computation of branch angles. The detailed modeling results of each method in Tree2-6 are shown in Appendix Figs. A5-9.

2.4.3. Branch angle calculation

Branch angle is defined as the angle between two branches by the following equation:

$$\theta = \arccos \left(\frac{\langle \overrightarrow{AB}, \overrightarrow{AC} \rangle}{|\overrightarrow{AB}| \times |\overrightarrow{AC}|} \right) \quad (3)$$

where A is the bifurcation point of two branches, and B and C are the bifurcation points of two daughter-branches of A respectively.

2.5. Statistical analysis

To explore the influence of branch measurement position and branch measurement length on branch angle, we categorized branches into four groups according to the curvature of each branch: Group A are the branches that bend outward by at least 10° (curvature $\leq -10^\circ$); group B are the branches that bend outward between 10° and 0° ($-10^\circ <$

curvature $\leq 0^\circ$); group C are the branches that bend inward between 0° and 10° ($0^\circ < \text{curvature} \leq 10^\circ$); group D are the branches that bend inward by at least 10° (curvature $> 10^\circ$). Subsequently, we compared the mean of branch angles measured at different branch lengths.

The accuracy of the branch angle measurements was estimated using the concordance correlation coefficient (CCC) and root-mean-squared error (RMSE). CCC quantifies the agreement of observations from two sources, ranging from 1 (perfect concordance) and -1 (perfect discordance) (Nickerson, 1997). Additionally, the relationships between branch size, branch curvature, branch order and branch angle residual were analyzed through Pearson correlation analysis, and the statistical t -test was used to determine the significance level of each correlation in R language (Version. 4.2.2). ANOVA (analysis of variance) was used to analyze the differences between the branch angle errors in different orders obtained based on the automatic algorithm.

3. Results

3.1. Effect of branch measurement position on manual branch angle measurements in the field

Here, we compare branch angles of European beech obtained from different branch length positions. The results show (Fig. 5b, c, f, g) that for branches of group B and C, the difference in branch angle measured at different branch length positions is not substantial. However, in the case of group A and D (Fig. 5a–d, e, h), significant differences are observed in the branch angles measured at different branch lengths. As the measured length increases, the difference in the branch angles increases, and the difference between them can be as high as 20° .

The results in Fig. 6 show the surface branch angle in relation to center branch angle and reveal minimal differences in branch angles between the branch center and the branch surface (RMSE $< 1.19^\circ$; CCC =

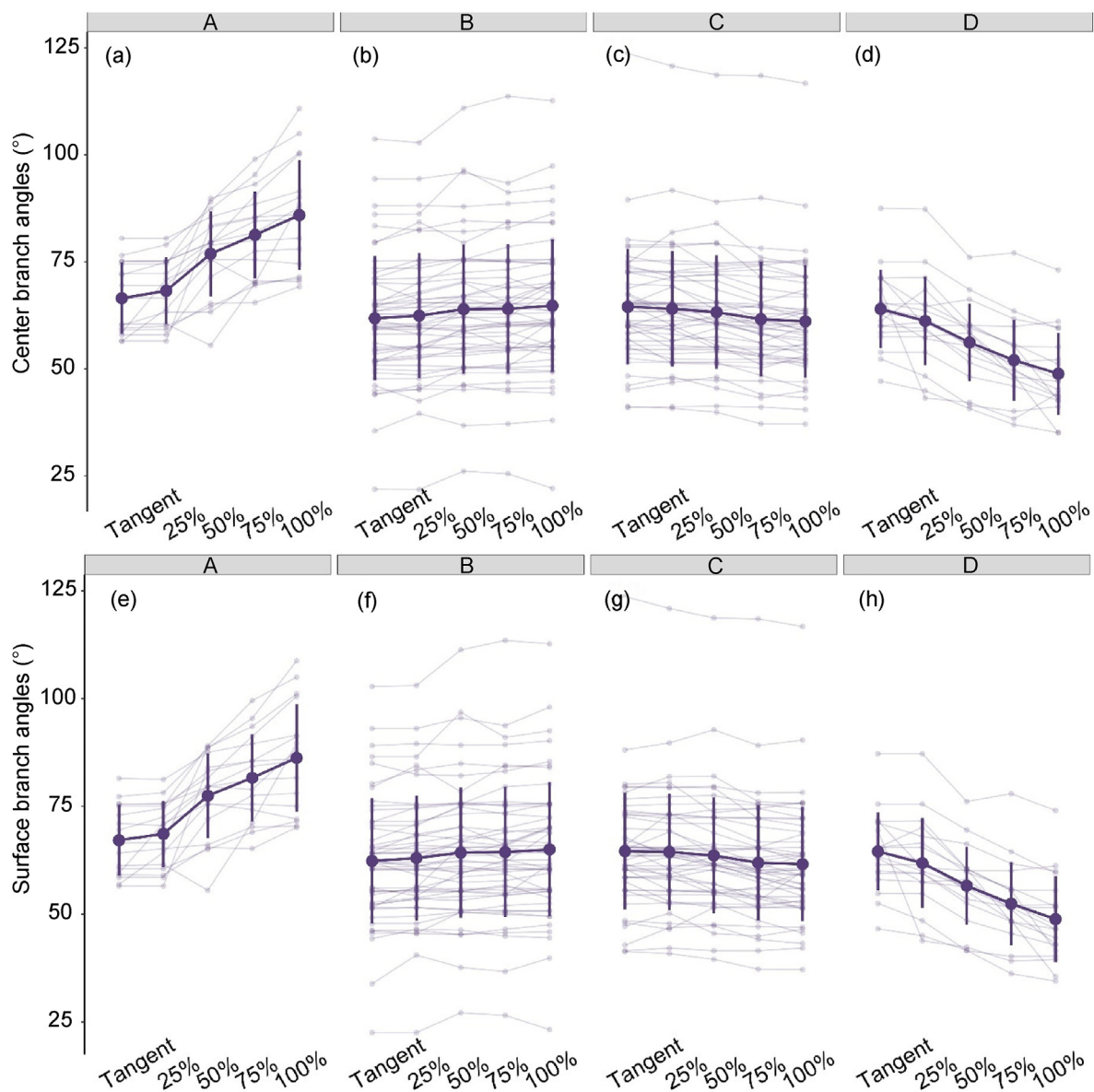


Fig. 5. Branch angles slope chart with mean plot and error bar. (a) is the branch angles that bend outward by at least 10° (curvature $\leq -10^\circ$), (b) is the branch angles that bend outward between 10° and 0° ($-10^\circ < \text{curvature} \leq 0^\circ$), (c) is the branch angles that bend inward between 0° and 10° ($0^\circ < \text{curvature} \leq 10^\circ$) and (d) is the branch angles that bend inward by at least 10° (curvature $> 10^\circ$). Tangent, 25%, 50%, 75% and 100% is the branch angle at tangent, 25%, 50%, 75% and 100% of branch length position respectively. (top) is the branch angle measured at branch center, (bottom) is the branch angle measured at branch surface.

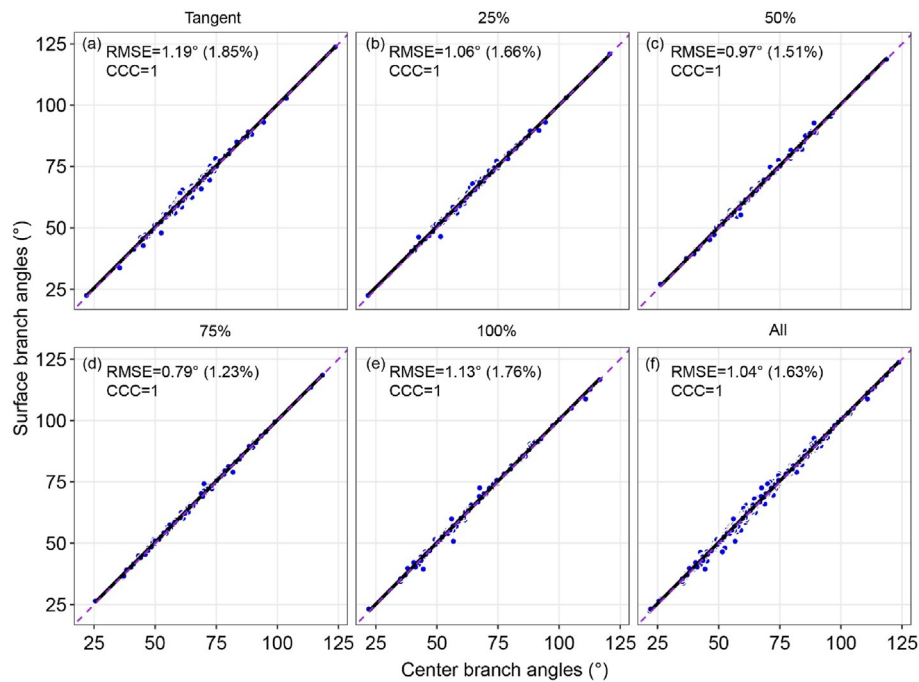


Fig. 6. A comparison of branch angles measured at branch center and surface. RMSE refers to the root-mean-squared error. The values in brackets are the percentage RMSE. CCC refers to the concordance correlation coefficient between center branch angles and surface branch angles. The solid line in each panel is a linear regression. The dashed line in each panel is a 1:1 relationship.

1), irrespective of the branch lengths considered for the measurements.

3.2. The evaluation of manual branch angle measurements on TLS data

A branch angle comparison between manual measurements in the field and manual measurements on TLS data at five branch length locations per branch (Fig. 7) shows the high accuracy of manual branch angle measurements on TLS data (RMSE: [3.57°, 4.18°], CCC: [0.95, 0.97]). Specifically, for branch angles measured at 25% of the branch length, the highest accuracy is achieved with a RMSE of 3.57° (5.65%) and CCC of

0.96.

Furthermore, we find that the difference in branch angles between manual measurements in the field and manual measurements on TLS data is not correlated with branch size (ranging from 3.76 to 40.21 mm) and branch curvature (ranging from -30.2° to 34.35°) (Appendix Figs. A1, A2).

3.3. Evaluation of automated algorithms of branch angles

We use four automated algorithms (LBC, S-LBC, aRchiQSM and

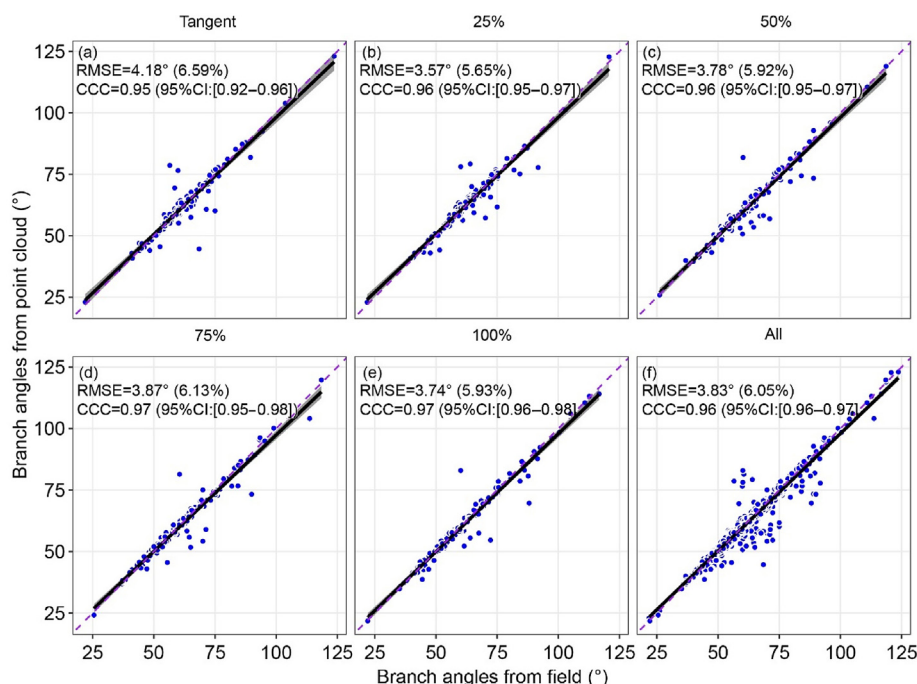


Fig. 7. The comparison of branch angle measurements from TLS and field. RMSE refers to the root-mean-squared error between manual measurements in the field and manual measurement on TLS data. The values in brackets are the percentage RMSE. CCC refers to the concordance correlation coefficient between manual measurements in the field and manual measurements on TLS data. The values in brackets after CCC are 95% confidence intervals. The solid line in each panel is a linear regression. The dashed line in each panel is a 1:1 relationship. The gray area is the confidence interval.

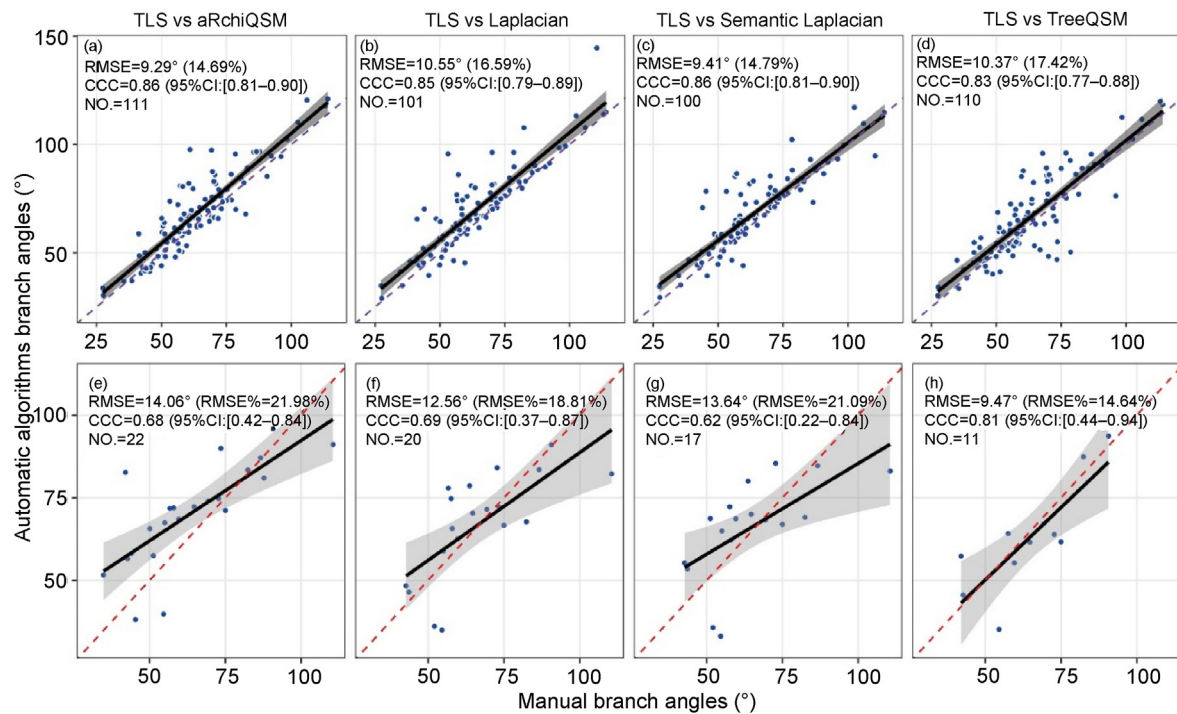


Fig. 8. Branch angles evaluation using four automated methods. (a), (b), (c), and (d) show the comparison of manual branch angle measurements on TLS data with automatically extracted branch angles using aRchiQSM, LBC, S-LBC, and TreeQSM, respectively, after manual leaf points removal. (e), (f), (g), and (h) display the same comparison based on automatic leaf points removal from TLS data. RMSE refers to the root-mean-square error between manual methods and automated methods. The values in brackets are the percentage RMSE. CCC refers to the concordance correlation coefficient between manual methods and automated methods. The values in brackets after CCC are 95% confidence intervals. NO. refers to the number of identified branch angles. The solid line in each panel is a linear regression. The dashed line in each panel is a 1:1 relationship. The gray area is the confidence interval.

TreeQSM) to extract branch angles (Fig. 8a–d). When comparing these automated methods to manual branch angle measurements from TLS data, the performance of the four algorithms is similar, with RMSE (CCC) values of 10.55° (0.85) for LBC, 9.29° (0.86) for S-LBC, 9.41° (0.86) for aRchiQSM, and 10.37° (0.83) for TreeQSM. aRchiQSM has the highest accuracy, followed by S-LBC, LBC, TreeQSM. Among the 124 branch point cloud data collected, aRchiQSM, TreeQSM, LBC, and S-LBC retrieve 111, 110, 101, and 100 branch angles, respectively (Appendix Table A1). Compared with the two Laplacian algorithms, both QSMs algorithms retrieve more branches.

After applying the automatic wood-leaf separation algorithm, the number of detected branch angles significantly reduces across all four algorithms (Fig. 8e–h). The number of branch angles identified by aRchiQSM, LBC, S-LBC, and TreeQSM are 22, 20, 17, and 11, respectively. Additionally, except for TreeQSM (RMSE = 9.47°), the accuracy of aRchiQSM (RMSE = 14.06°), LBC (RMSE = 12.56°), and S-LBC (RMSE = 13.64°) also decreases compared with manual leaf points removal data.

Further analysis reveals significant differences in branch angles for aRchiQSM, S-LBC and LBC across various branch orders, while TreeQSM exhibits no variations among different branch orders (Appendix Fig. A2). Additionally, the aRchiQSM, S-LBC and LBC error demonstrates a negative relationship with the size of the branches, whereas the errors for TreeQSM are not influenced by branch size (Appendix Fig. A3). These findings suggest that aRchiQSM, S-LBC and LBC is susceptible to the influence of branch size and order, whereas TreeQSM is not affected by variations in branch size and order.

4. Discussion

4.1. Manual branch angle measurements in the field

The difficulties in field measurements have led to the adoption of different branch lengths in various studies, ranging from 5 cm to the

entire length of the branch (Ding et al., 2022; Kint et al., 2010; Lintunen and Kaitaniemi, 2010). Our results highlight that the choice of branch length significantly influences branch angle measurements, particularly as differences in branch angles measured at different branch lengths increase with rising branch curvature. Given the prevalence of curved branches in forests, surveyors must account for these variations introduced by the choice of branch length in branch angle measurements. Although surveyors can choose different branch lengths for measuring branch angles depending on the purpose of the study, it is important to note that a uniform branch length needs to be used throughout the study. In contrast, measurements of the branch surface and branch center exhibited no significant difference in branch angle, regardless of the branch length used. Therefore, investigators can choose between different branch surfaces or branch center depending on the difficulty of measuring different branch angles. This consistency aligns with our expectations, as the size disparity between the end and the beginning of branches is not substantial. From a geometric perspective, the position of branch measurement does not significantly impact branch angle measurement outcomes. In summary, while surveyors can opt for different branch positions when measuring branch angles using traditional methods, careful consideration of branch length is essential to ensure accuracy in measurements, especially with curved branches.

4.2. Manual branch angle measurements on TLS data

Occlusion has been identified as a major source of uncertainty in the extraction of forest structure traits (Schneider et al., 2019). Occlusion can be mitigated by some means, such as the use of multiple scan position approach, multiple returns scanners, and scanning in leaf-off conditions (Lau et al., 2019). Despite the design of specific scanning locations for target branches to mitigate occlusion, 13 branches remained unscanned due to the occlusion caused by surrounding leaves and branches. Overall, manual branch angle measurements on TLS data proved highly accurate,

with an error (RMSE) of only about 3.8° compared to manual branch angle measurements in the field. Although a residual error of approximately 3.8° exists, it is conceivable that the actual error is even smaller, potentially attributable to manual branch angle measurement errors in the field. Curved branches and branches exceeding the length of the protractor (60 mm) posed challenges for manual branch angle measurements in the field due to difficulties in achieving perfect alignment between the branch and the protractor sides.

We demonstrated that the accuracy of manual branch angle measurements on TLS data is very high, even if the branch size is very small. However, this does not imply a high capability of capturing branch angles in TLS. This is because for small branches, they are not easily detected by TLS because they are surrounded by leaves. A commonly employed solution is to scan trees in leaf-off conditions. Additional findings indicate that the accuracy of manual branch angle measurements on TLS data remain unaffected by variations in branch curvature and size. The quality of point cloud data is more likely to be affected by the TLS instrument, instrument parameters and scanning configuration (Abegg et al., 2021; Wilkes et al., 2017). By configuring reasonable scanning locations, RIEGL VZ-400i can collect point cloud information of small-sized tree branches (Morhart et al., 2024; Wilkes et al., 2021).

4.3. Automatic extraction methods of branch angles

In this study, four algorithms were employed for the automated retrieval of branch angles and the results showed good accuracy (RMSE: $[9.29^\circ, 10.55^\circ]$, CCC: $[0.83, 0.86]$). Previous research has showcased good performance of QSMs for other tree characteristics, such as trunk volume (Calders et al., 2015; Du et al., 2019; Fan et al., 2020). Both QSMs we tested here showed good accuracy in branch angle estimates, with aRchiQSM having the highest accuracy. In the case of aRchiQSM, we do not need to fit geometric shapes (i.e. cylinders) to the tree point cloud, bypassing the modeling errors associated with fitting geometric shapes. There are other algorithms to reconstruct the QSMs (Du et al., 2019; Fan et al., 2020; Yang et al., 2024), and the results might be different. We found that S-LBC has slightly higher accuracy than LBC, which is consistent with our expectations. As an improved version of LBC, S-LBC can obtain better skeleton structures from point clouds by weighting branches of different sizes (Cao et al., 2010; Meyer et al., 2023). It is noteworthy that all four algorithms can not retrieve all branch angles that are present in the point cloud. This issue, documented in existing studies (Wilkes et al., 2021; Winberg et al., 2023; Yrttimaa et al., 2023), emphasizes the need for future algorithms to enhance the retrieval capabilities of branches. Compared with Laplacian algorithms, both QSMs methods retrieved more branch angles. We collected the TLS data in leaf-on conditions. Part of point cloud data of some branches were occluded, and the Laplacian algorithm was unable to retrieve the branches from the missing points (Cao et al., 2010).

An exploration of branch angle errors revealed that the accuracy of aRchiQSM, S-LBC and LBC is affected by branch size and order, whereas the accuracy of TreeQSM is not related to branch characteristics. Prior research (Cao et al., 2010; Meyer et al., 2023) consistently demonstrates LBC's susceptibility to branch size, particularly when addressing branches with considerable size differences, leading to challenges in precisely identifying bifurcation points of a pair of branches. Our findings align with a study by Li et al. (2020), indicating that LBC's accuracy diminishes for high-order branches compared to low-order branches. S-LBC achieves higher accuracy relative to LBC by weighting branches of different sizes, however, it is still affected by branch size, which may be related to the shortcomings of the Laplacian algorithm itself (Cao et al., 2010; Meyer et al., 2023). For aRchiQSM, which contains 3 parameters, users are required to adjust different parameter combinations for trees of different sizes to obtain the best fitting results. Although we selected the parameter combinations by visual inspection of the QSM, our results show that aRchiQSM is affected by the size of the branches. This may be due to the inherent limitations of the aRchiQSM. Conversely, TreeQSM is

unaffected by branch size and order. The TreeQSM approach, which first segments the point cloud into trunks and individual branches and then performs geometric reconstruction (Raumonen et al., 2013), may contribute to this result to some extent. However, it should be emphasized that this approach requires accurate bifurcation identification. Although aRchiQSM has higher accuracy than TreeQSM, it is more sensitive to changes in branch size. As the branch size increases, the error of aRchiQSM will increase (Appendix Fig. A3). Therefore, TreeQSM may perform better than the other algorithms when dealing with large trees that contain a large number of branches of various sizes. It is necessary to collect more data to verify this hypothesis.

Upon comparing three branch angle measurement methods, it was observed that while manual measurements in the field face limitations in handling a diverse array of branches and can only measure a subset of available branches, manual measurements on TLS data offer accuracy comparable to manual measurement in the field and enable the manual measurement of almost all branch angles within the canopy. Automatic TLS measurement allows for rapid and large-scale acquisition of branch angles with good accuracy. It should be noted that our branch angle samples come from the lower part of the canopy. Results for branches in the middle and upper parts of the canopy may differ somewhat. According to the working principle of TLS, the laser spot reaching the upper part of the canopy is larger, the distance between adjacent laser spots is greater, and the branches are more susceptible to occlusion, resulting in poorer data quality (Abegg et al., 2021; Schmitz et al., 2020; Wilkes et al., 2017). Future research needs to enhance our understanding of this aspect. Moreover, our study sample includes small and medium trees for one species, warranting caution in extrapolating our measurements to larger tree sizes and other tree species. Different tree species exhibit varying crown complexities, which affects the quality of TLS data. Our study focused on European beech, characterized by a complex crown structure and generally thin branches. In species with simpler crown structures, such as oak, the accuracy of branch angle measurements may be higher. For taller trees, branches in the upper crown are often more occluded, leading to lower-quality point cloud data in these regions. As a result, further research is necessary to evaluate the accuracy of branch angle measurements in larger trees and other species. Finally, TLS data used for branch angle extraction should be collected in an environment with minimal wind speeds, because ghost point will result in a large number of branch angles that cannot be extracted from TLS data.

In leaf-on conditions, fully automatic extraction of branch angles from TLS data is no longer useful. This is primarily due to two challenges: first, leaf occlusion prevents TLS data from fully capturing branch structures; second, the point cloud data retains leaf points that are difficult to automatically remove. While many wood-leaf separation algorithms exist (Hui et al., 2021; Tan et al., 2021; Tian and Li, 2022; Vicari et al., 2019; Wang et al., 2020), the wood point clouds they produce still contain some leaf points. Additionally, separating small branches remains problematic. A previous study suggested that GBSeparation performs better in identifying small branches compared to other methods (Tian and Li, 2022). However, our results indicate that GBSeparation still fails to capture most small branches, leading to the identification of only about 20 branch angles across four algorithms. The presence of leaf points in the wood point cloud also hinders the automatic extraction of branch angles, as these points can cause misidentification of bifurcations. Therefore, challenges remain in extracting branch angles using fully automatic methods in leaf-on TLS data. When comparing results between leaf-on and leaf-off data, leaf-off TLS data proves more suitable for automatic branch angle extraction due to the significantly higher quality of the point cloud.

In this study, we designed a specialized scanning protocol to improve the quality of TLS data for target branches. When applying our findings to other scanning protocols, the accuracy of branch angle extraction may decrease, as scanning protocols greatly influence TLS data quality. In forest environments, single-scan and multi-scan protocols are commonly used. Single-scan protocols often result in severe occlusion, with most

branch information lost, making the data only suitable for extracting a limited number of branch angles. While multi-scan protocols help reduce occlusion effects, the upper canopy remains significantly impacted, especially under leaf-on conditions. Even with a high density of scan locations, many small branches are still missing. Additionally, multi-scan protocols may capture incomplete point cloud data for some branches, leading to reduced accuracy in branch angle extraction.

4.4. Outlook for automatic measurements methods of branch angles

Although our study demonstrates the good performance of the automated measurements method in automatically retrieving branch angles, the automated measurements can still be improved. During TLS data processing, we manually segmented individual trees and removed leaves to exclude the influence of automatic preprocessing methods on the automatic extraction of branch angles. Future research should focus on exploring the influence of leaves on branch angles to comprehensively evaluate the feasibility of automatic branch angle retrieval. We observed large errors in some branch angles (Appendix Fig. A3) because the bifurcation points of these branches were incorrectly identified. To enhance the precision of the automated algorithms, future algorithms should focus on refining the recognition of bifurcation points. Moreover, point cloud quality is an important factor affecting the extraction of forest structure features (Morhart et al., 2024; Pueschel et al., 2013; Saarinen et al., 2017), and in our study sample, some branch angles had incomplete point cloud data. Improving the quality of point cloud data by reducing occlusions will help to improve the accuracy of the automatic algorithms. In addition to improving the accuracy of the automatic algorithms, the ability to retrieve branches should also be improved.

5. Conclusion

This study evaluates different methods to measure branch angles of European beech from tree point clouds in a European forest. Our study demonstrates that TLS point cloud data can accurately capture branch angle information. Automated algorithms are effective tools to retrieve a large number of branch angles from forest leaf-off TLS data. The automated measurement methods of branch angles provide an unprecedented tool to study the variation in branch angle distribution. Quantifying the temporal and spatial variation in branch angle distribution will likely give insight into the mechanisms employed by trees to optimize light interception.

CRedit authorship contribution statement

Xi Peng: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Kim Calders:** Writing – review & editing, Supervision, Conceptualization. **Louise Terryn:** Writing – review & editing, Methodology, Data curation. **Hans Verbeeck:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Data availability

Data will be made available on request.

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Declaration of competing interest

The authors declare that they have no known competing financial

interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.fecs.2024.100279>.

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