



Boundary conditions for studying branch-scale tree growth strategies using tree quantitative structure model time series[☆]

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ABSTRACT

Advances in Light Detection and Ranging (LiDAR) technology, along with point cloud modeling techniques like Quantitative Structure Models (QSM), have improved the accuracy of non-destructive above-ground tree biomass estimation. However, branch-level tree growth analysis using QSM time series remains underexplored due to challenges in data quality and methodology. This study investigates the boundary conditions in terms of data and species to facilitate robust QSM generation, which could enable branch-level growth analysis using multi-temporal LiDAR data and QSM. A multi-scan terrestrial laser scanning dataset and a dataset from a tower-based system were used to assess the impact of data acquisition setup and data quality on QSM reconstruction for birch (*Betula pendula*), pines (*Pinus sylvestris*), and spruces (*Picea abies*). The results show that reliable QSMs for detecting branch-level growth require a minimum spatial resolution of approximately 500 pts./m³ with a uniform point density, a maximum uniform 3D point distance of 2 cm, and gaps smaller than around 20 cm. Although smaller spherical noise clusters can be removed using denoising techniques, larger and denser noise clusters (e.g., > 9500 points within 1 m radius) are more likely to be misidentified as additional branches. Foliage removal methods risk modeling accuracy by inadvertently removing woody points. Regarding species, birches were more accurately modeled than pines and spruces. While QSMs are reproducible for single time points, comparing branches over time is challenging due to inconsistencies in modeled branching order and scanner positioning. Nonetheless, tree-level QSM metrics remain statistically consistent, revealing diverse growth strategies within and across species.

1. Introduction

Accurate estimation of aboveground biomass (AGB) accumulation and understanding its allocation at the individual-tree level are essential both ecologically and economically, particularly for sustainable forest management and biodiversity conservation. Ecologically, achieving carbon neutrality is crucial for mitigating global climate change and reducing rising atmospheric carbon dioxide levels. This requires a comprehensive understanding of the carbon cycle and carbon sequestration processes (Lamont et al., 2020). Economically, more precise

measurements of biomass accumulation and carbon sequestration are valuable for the management of commercial timber and participation in carbon markets (Ghaffariyan et al., 2017). However, non-destructive methods for monitoring tree growth and AGB allocation remain a significant technical and scientific challenge due to the need for continuous, highly accurate, and detailed measurements. Consequently, the ability to assess forest resilience, biodiversity conservation efforts, and adaptive forest management strategies are limited. Light Detection and Ranging (LiDAR), a.k.a., Laser Scanning (LS), particularly when acquired from a ground-based, close-range perspective, is increasingly

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recognized as a powerful tool for non-destructive *in situ* AGB estimation, with applications in forest inventory, ecosystem monitoring, and habitat structure analysis.

The potential of LS systems in estimating tree-level biomass was first explored in the early 2000s. LS sensors were shown to accurately estimate biomass across various forest types, particularly at the plot scale, by using allometric models for indirect estimation. Studies from this period demonstrated that LS could extract key forest and tree metrics with accuracy comparable to traditional field-based methods (White et al., 2016). These findings established LS systems as effective data sources for estimating AGB, supporting its integration into forest carbon accounting systems and conservation initiatives.

In the past decade, biomass estimation at the tree level has advanced significantly due to improvements in LS technology and the development of automated data processing and modeling techniques. A key advancement has been the development of the Quantitative Structure Model (QSM), which represents a tree's stem and branch structure using cylinder-based models derived from LS point clouds (Raumonen et al., 2013), and therefore provides direct access to a tree's wood volume. QSMs have become a valuable tool for analyzing AGB at the individual-tree level, offering higher resolution and greater accuracy compared to traditional area-based methods that rely on coarse statistical models based on parameters such as canopy height and basal area. Terrestrial Laser Scanning (TLS) provides high-quality point clouds with high spatial resolution and geometric accuracy and is regarded as a standard data source for tree QSM generation.

Several studies have demonstrated the effectiveness of QSMs derived from TLS point clouds (Åkerblom and Kaitaniemi, 2021). Their ability to quantify fine-scale structural traits makes them particularly useful for sustainable forestry and biodiversity monitoring. For example, Calders et al. (2015) showed that combining TLS data with QSM (TLS + QSM) provided direct estimates of tree volume and AGB for a native Eucalypt Open Forest in Victoria, Australia, with less than 10 % overestimation compared to destructive biomass references, whereas allometric equations showed lower agreement, with concordance correlation coefficients (CCC) ranging from 0.68 to 0.78. Similarly, De Tanago et al. (2017) validated the accuracy of AGB estimates across tropical forest sites in Peru, Indonesia, and Guyana from TLS + QSM, showing a CCC of 0.95 compared to destructive harvest measurements, outperforming allometric models (CCC 0.89–0.73). These studies validated the TLS + QSM approach for tree-level biomass estimation and highlighted the importance of accurate data preprocessing, including tree detection and segmentation, for ensuring reliable QSM accuracy.

However, despite these advancements, the application of QSM remains limited due to the requirement of highly dense and complete point cloud data. Most QSM-based studies have used tree-scale multi-scan TLS data, where a single tree is scanned from multiple directions and the resulting scans are merged. Such a demanding data acquisition scheme is economically and computationally costly. Therefore, interest is rising to investigate the possibility of QSM reconstruction using degraded LS data from various close-range systems, such as plot-scale multi-scan TLS, handheld LS (HLS), and unmanned aerial vehicle (UAV) LS (UAV-LS), which may include occlusions, noise, or distortions. Wang et al. (2019) emphasized the inherent uncertainties of LS data acquisition, particularly related to scanning geometry and resolution. Moreover, errors can arise during critical data preprocessing steps, such as detecting and segmenting individual trees, especially when generating QSMs. Morhart et al. (2024) showed that scanning distance significantly impacted the accuracy of branch length and volume estimates, with scanning distances exceeding 45 m causing substantial errors in branch volume estimates due to the larger laser beam size and reduced resolution. Brede et al. (2019) observed that UAV-LS point clouds were less accurate in dense forests with smaller trees, while Ye et al. (2019) highlighted that their data resolution and overall accuracy require further refinement when combined with QSMs. Recent studies suggest that the TLS + QSM approach shows promise for tracking AGB changes at the branch level.

QSMs efficiently quantify various structural traits of trees, such as the diameter, length, and orientation of branches. By capturing fine-scale branching structures, QSMs allow for the study of branch-level growth dynamics in individual trees, especially when structural differences between bi-temporal QSMs can be quantified. This allows for a more comprehensive analysis of how biomass is distributed over time, improving the understanding of species-specific growth patterns and adaptive responses to environmental conditions.

However, challenges persist, specifically considering the feasibility and reliability of QSM generation for different types of trees using different data sources. For instance, Kaasalainen et al. (2014) demonstrated that branch length could be estimated with 5 %–10 % uncertainty using TLS + QSM. The study also emphasized that more accurate estimation of complex tree parameters, such as biomass over time, requires improved data quality through noise reduction and increasing completeness. Lau et al. (2018) noted that branch diameters between 20 and 60 cm were overestimated by 8 %, while branch lengths greater than 50 cm were slightly overestimated by 1 %. Liang et al. (2018) reported challenges in accurately extracting branch information even from high spatial resolution TLS data, and Hui et al. (2021) highlighted that Norway spruce poses challenges due to its tiny branches, complicating the estimation of branch attributes. Demol et al. (2022) concluded that TLS + QSM tends to overestimate small branches, highlighting the limitations of this method in accurately capturing branch volume. Morhart et al. (2024) further investigated the effects of scanning distance on the accuracy of length and volume estimates of branches under partially controlled laboratory conditions. They found that the cumulative length of the reconstructed branches, with an average length of 2.6 m, was underestimated by -75 % at a scanning distance of 45 m, while individual volumes were overestimated by 539 %. The discrepancies in volume estimates were attributed to an increased laser beam size, while the decreased resolution affected length estimates.

Because of these data and processing challenges, high-resolution AGB change maps remain scarce, particularly over shorter time periods (e.g., less than 10 years), due to the difficulty in detecting AGB changes at fine scales (Turton et al., 2022), limiting their application in tracking forest recovery, disturbance impacts, and adaptive management planning. Consequently, using multi-temporal LS data for biomass change estimation becomes an even more challenging task, due to additional issues such as multi-temporal registration accuracy (Okuy et al., 2019; Liang et al., 2022). Moreover, few studies have investigated branch-level biomass change using multi-temporal QSMs, despite the increasing recognition of branch growth as a key factor in overall biomass dynamics (e.g., Pyörälä et al., 2018; Junttila et al., 2022).

In this context, our study thoroughly investigated the boundary conditions from both the data and tree structure perspectives for achieving ideal QSM generation, which could facilitate the multi-temporal LS + QSM approach for estimating tree growth dynamics at the branch level. The main goal of this study is to inspect the data quality thresholds (boundary conditions) required for LS point cloud data from different systems to enable effective QSM reconstruction and to explore the feasibility of tracking branch-level growth using QSMs generated from multi-temporal LS datasets. Considering the higher affordability and convenience of acquiring multi-temporal LS data using UAV-LS systems, and the higher data quality of TLS systems, this study investigates the performance of multi-temporal QSMs generated using standard plot-scale multi-scan TLS dataset and using UAV-LS-level dataset acquired by a permanent LS forest observation system (PLS) installed on a flux tower. The PLS dataset was used to resemble UAV-LS datasets, considering its similarity of the viewing geometry and data quality with low-altitude UAV-LS systems. To study the influence of species-induced tree structural variances, this study included three most commonly distributed boreal tree species: Scots pine (*Pinus sylvestris* L.), silver birch (*Betula pendula* Roth), and Norway spruce (*Picea abies* H. Karst.).

The merit of our work lies in identifying the key challenges that arise

when data quality is suboptimal and tree structures are not clearly recorded, as well as in establishing the minimum data quality requirements for generating workable QSMs for different species.

2. Datasets

Two distinct LS data acquisition setups were evaluated to assess the impact of viewing geometry on data quality, and consequently, on the quality of QSM generation. Fig. 1 shows the study areas on a map and photographs of the sensors in the forests.

The first setup, referred to as multi-scan TLS (Fig. 1e), utilized a configuration of five stations (one center and four corner stations) for data collection over forest sample plots. The multi-scan approach produces higher-quality TLS point clouds compared to other terrestrial mobile systems, such as backpack and handheld systems (Bauwens et al., 2016; Liang et al., 2016). The second setup involved a long-range LS system fixed on a flux tower, observing the forest from above the canopy. This configuration serves as an approximation of high-quality above-canopy LS point clouds, similar to those obtained using UAV-LS systems. Together, these two setups represent typical close-range data acquisition scenarios: multiple viewpoints versus a single viewpoint, and ground perspective versus low-altitude aerial perspective. Table 1 provides an overview of the LS data acquisition setups and the resulting point cloud characteristics. In the following sections, the multi-scan TLS setup will be referred to as TLS, and the fixed tower LS setup will be referred to as PLS (Permanent Laser Scanning).

2.1. Fixed viewpoint data from a permanent laser scanning station

The PLS dataset in this study was collected from the permanent LiDAR Phenology station (LiPhe) located at the Hyytiälä Forest Station in Hyytiälä, Finland. The station is equipped with a RIEGL VZ-2000i (RIEGL GmbH, Horn, Austria) laser scanner protected by a weather-protection hood to ensure continuous outdoor measurements. The scanner is installed near the top of a flux tower, 30 m above the ground, and observes a forest area of approximately 263 m × 169 m. The LiPhe station can continuously capture the 3D structure of at least 400 trees with less than 1 cm 3D point spacing on an hourly basis, producing hyper-temporal, high-resolution 3D tree digitization time series

Table 1

LS collection setups and data attributes.

	TLS 2014	TLS 2019	PLS 2020–2021
Scanner	Leica HDS6100	Leica RTC360 3D	RIEGL VZ-2000i
Type of scanner	Time-Of-Flight	Time-Of-Flight	Time-Of-Flight
Range	79 m at 90 % albedo, 50 m at 18 % albedo	130 m	400 m (usable trees)
Angular resolution	0.018°	0.009°	0.006°
Point spacing	15.7 mm at 25 m from the scanner	3 mm at 10 m from the scanner (~7.5 mm at 25 m)	10 mm at 100 m from the scanner (~2.5 mm at 25 m)
Coverage area	37 32 m × 32 m plots	37 32 m × 32 m plots	263 m × 169 m
Wavelength	650–690 nm	1550 nm	1550 nm
Max. field-of-view (vertical/horizontal)	310° / 360°	300° / 360°	100° / 360°
Number of scans	5 per plot	5 per plot	1 per hour
Distance measurement accuracy	±2 mm at 25 m from the scanner	1 mm + 10 ppm (1.25 mm at 25 m)	3 mm at 100 m from the scanner (0.75 mm at 25 m)
Scanning frequency	508 kHz	2000 kHz	12,000 kHz

(Campos et al., 2021). This unique dataset provides fine-scale observations of diverse tree structures and features within forest environments over extended periods. The data is available from Wittke et al. (2024). For this study, we selected well-represented trees to ensure that the data were usable for analysis.

The PLS dataset includes two time series, along with data from other trees that were tested. Time Series I contains point clouds from a total of 32 time points (May 2020 to September 2021), with an average interval of two weeks (two scans per month). Time Series II consists of point clouds from 30 time points (April 2020 to July 2021). The point clouds were captured across a wide range of times throughout the day from 6 AM to 2 AM. Most scans were collected in the morning (6–12 AM), with the highest frequency around 10 AM. Some point clouds were captured during the afternoon, evening, and night. The point clouds were acquired under optimal weather conditions, including no precipitation, no snow, and wind speeds below 3 m/s, based on local weather data from

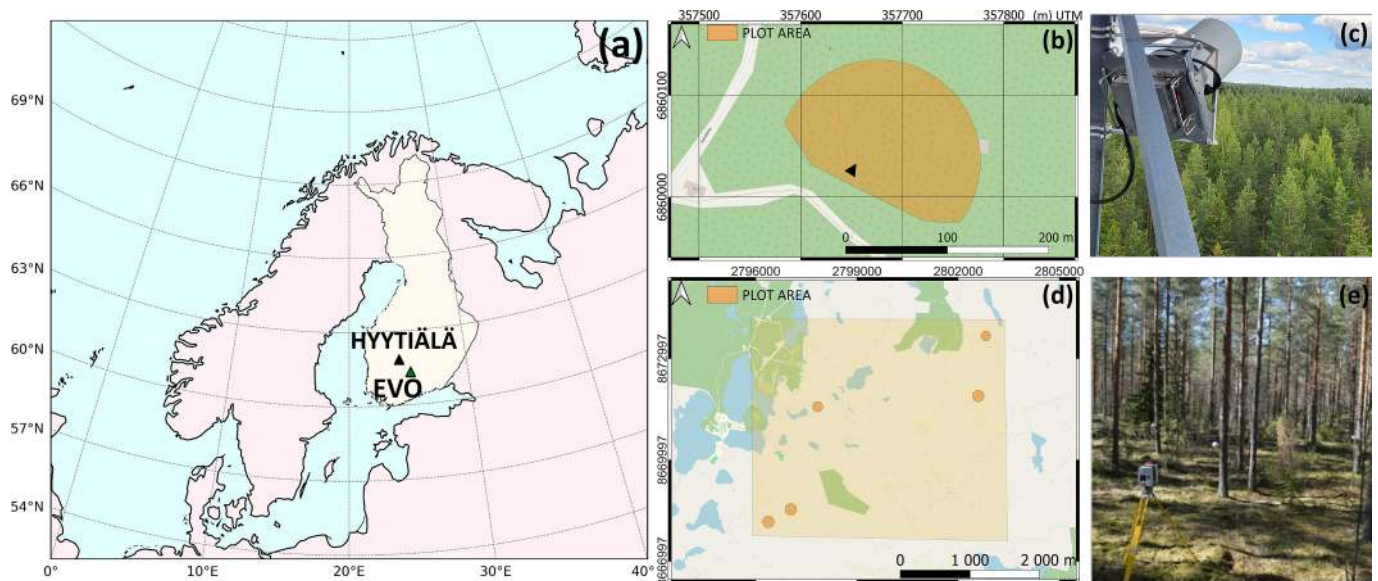


Fig. 1. A – Locations of the PLS site (Hyytiälä) and the TLS site (Evo) in Finland, represented by black and green triangles, respectively. B – Scanned area in Hyytiälä, displayed as an orange plot in the ETRS89/TM35FIN coordinate system. The black triangle indicates the PLS scanner location. C – PLS scanner in Hyytiälä and the surrounding forest. D – Location of Evo plots (orange circles), also shown in the ETRS89/TM35FIN coordinate system. E – TLS scanner and the surrounding forest environment in Evo. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the Station for Measuring Ecosystem-Atmosphere Relations (Hari et al., 2013). Thus, the PLS dataset supports temporal consistency analyses of AGB estimation over time by combining LS time series and QSM.

The PLS dataset is included in this work especially to investigate the boundary data quality requirements related to temporal resolution and completeness, given its single point of view. The PLS data captured more canopy information, resembling a near-ground, above-canopy UAV-LS system, where considerable occlusion for tree-level information exists. Additionally, the longer target-to-scanner distance and various environmental disturbances result in a relatively lower signal-to-noise ratio compared to ordinary ground-based TLS systems, potentially compromising data quality.

2.2. Five-station plot-scale multi-scan TLS

The multi-scan TLS dataset used in this study represents a standard TLS setting, as it compensates for incomplete tree-level information by using multiple viewpoints without exhaustive scanning. The dataset was collected in Evo, Finland, during two field campaigns in 2014 and 2019, both of which used the five-station setup, with one scan taken from the center of each sample plot, complemented by four additional scans from quadrant directions (Liang et al., 2018; Yrttimaa et al., 2020), ensuring thorough coverage and representation of the forested landscape. However, it is important to note that parts of the tree canopies were sometimes not captured, as the scanning was conducted from beneath the canopy at ground level. The scanning equipment used varied between the 2014 and 2019 datasets: the Leica HDS6100 phase-shift scanner was used in 2014 (Liang et al., 2018), and the Leica RTC 360 3D time-of-flight laser scanner was used in 2019 (Yrttimaa et al., 2020). The plot size was 1024 m² in 2014 and 380.1 m² in 2019. In 2014, the plots were 32 m × 32 m rectangles, while the plots became circular with an 11-m radius in 2019. The change from rectangular to circular plots was to achieve more comparable point clouds between 2014 and 2019. This is because the overall quality of the 2014 dataset is slightly poorer, because the auxiliary scans were located further away from the plot center than in 2019.

3. Methods

This section presents the methods used in this study for the processing pipeline, which comprises two main chains: (I) from raw point clouds to individual tree point clouds (Section 3.1), and (II) from individual tree point clouds to QSM generation (Section 3.3; Fig. 2). The selection of the individual tree dataset is presented in Section 3.2. Subsequently, we describe the method to quantify branch-scale growth (Section 3.4). The experimental design to address the key research questions of this study is presented in Section 3.5.

3.1. Processing pipeline I: from forest plot to individual tree point clouds

It is important to highlight that, when the study focuses on quantifying changes at the scale of small tree structures, e.g., branches, it is essential to ensure that the detected structural changes reflect actual

changes in the target structures rather than artifacts caused by processing errors in the long processing pipeline, such as misregistration among datasets from different perspectives or time points, or erroneous modeling due to incorrect individual tree delineation or wood separation.

Apart from rare cases where a specific target tree was exhaustively digitized using multiple scans (e.g., Bremer et al., 2012), LS data collection typically targets forest areas at least the size of a sample plot. Thus, there is a common requirement of a long preprocessing pipeline to enable tree QSM generation and multi-temporal QSM comparison, which includes the fine registration of datasets from different time points, the individual tree delineation (i.e., individual tree detection and 3D segmentation from point cloud), the separation between wood and foliage components, and the QSM generation from the woody point cloud of individual trees. Both the PLS and TLS datasets followed a rigorous LS data processing protocol from plot-level to tree-level point clouds.

3.1.1. Data registration

Accurate registration of point clouds across spatial and temporal domains is crucial for reliably detecting and quantifying changes in tree structures. This includes the spatial registration among different TLS scans for a sample plot, and the temporal registration among different time points.

3.1.1.1. Registration of multi-scan TLS dataset. Artificial spheres were strategically positioned within the study area as reference targets to ensure precise alignment and integration of individual scans (Liang et al., 2018; Yrttimaa et al., 2020). The spheres were placed both inside and outside the plots, and there was an average of six targets per plot (Liang et al., 2018). The exact positions of the spheres in a global co-ordinate system (EUREF-FIN) were established using a Trimble R8 GNSS receiver with real-time kinematic correction as a reference base. A Trimble 5602 DR200+ total station was used for measuring the sphere center location. For the TLS dataset, cross-temporal tree registration was carried out using an automated approach, which matches the trees in two tree maps by simultaneously evaluating the XY planar tree locations, DBHs, and tree heights. Detailed descriptions of the matching approach are provided in the methods of evaluation section in Liang et al. (2018). Across all sample plots scanned in 2014, the average registration accuracy was 2.1 mm. Ground-truth data were collected through integrating field inventories and manual measurements from TLS data for evaluation.

Ground points of the TLS point clouds were identified using the ground classification algorithm in TerraScan (Terrasolid Ltd., Espoo, Finland) software that is based on a triangulated irregular network (TIN) densification algorithm (Liang et al., 2018). The algorithm uses local low points as initial points. More ground points were added to densify the TIN according to given parameters that were selected considering the general terrain shape and the potential density of the ground points (Axelsson, 2000). The same parameter setting was applied for all plots in the automated phase as the terrain shape can be regarded as relatively smooth in a plot scale, and non-ground objects with diameters larger

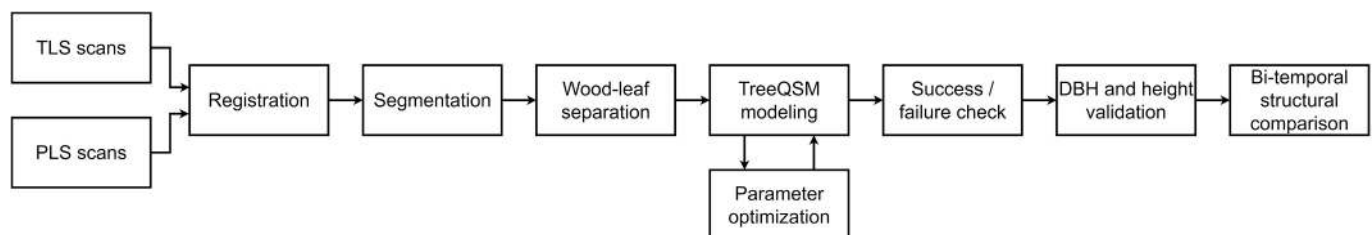


Fig. 2. Workflow diagram of LS data processing and TreeQSM. TLS and PLS scans were registered, segmented and separated into wood and leaf components. TreeQSM modeling with parameter optimization was followed by a success/failure check, DBH and height validation, and bi-temporal structural comparison.

than a predefined threshold of 63 cm were visually checked and manually removed (Liang et al., 2018). The threshold was defined based on a manual estimation of average stumps and stones found in the plots. Topographic variations were addressed by normalizing the Z-coordinates of above-ground heights within all point clouds to standardize elevation data for both 2014 and 2019 TLS data (Liang et al., 2018; Yrttimaa et al., 2020).

3.1.1.2. Registration of the PLS dataset. Even for the PLS dataset, where the point clouds from different time points were collected from a fixed location, misalignments still occur due to various environmental factors, such as intrinsic branch movements, seasonal canopy movement, and changes in water content (Campos et al., 2021).

The cross-temporal registration of the PLS point clouds was based on the stem positions. Therefore, the initial individual tree detection not only served to detect the trees but also helped in data registration. As mentioned, tree stems were identified in the point cloud using an automatic stem detection method from Liang et al. (2012). For more detailed information about the method, readers are recommended to consult the original paper.

Due to the fixed viewpoint and local origin of the scanner, misalignments between trees from different time points were minimal—less than 0.01 m in the PLS data—when stem locations were used to aid the cross-temporal registration. In this work, we use the PLS point clouds in the local reference system to avoid potential errors arising from georeferencing transformations.

3.1.2. Individual tree delineation

While automated individual tree delineation (ITD; i.e., detection and 3D segmentation) has seen significant advancements, fully relying on automated approaches can still be unreliable, particularly in complex forest stand conditions (Zhang et al., 2024). Therefore, to ensure accurate individual tree segmentation, we implemented a semi-automated, coarse-to-fine approach.

The initial coarse segmentation of individual point clouds was performed using a cylindrical buffer with a radius of 3.5 m around the detected stem coordinates derived using the stem detection method (Liang et al., 2012). This buffer exceeds the typical tree canopy cover and was used as a threshold to ensure the inclusion of complete canopy details. These coarsely segmented trees were then used as input for an unsupervised statistical approach to separate wood and non-wood components at the tree level (Shcherbacheva et al., 2023). This approach was applied to both PLS and TLS individual tree point clouds. Individual tree segmentation was performed using a custom Matlab script.

Subsequent fine segmentation was performed, when necessary, by manually removing noise from neighboring trees using CloudCompare (CloudCompare, 2021) to minimize errors from the individual tree segmentation preprocessing. It is important to note that individual tree segmentation can introduce significant errors, affecting data completeness, including both commission and omission errors.

3.2. Selection of individual tree point clouds

After the first part of processing, based on the quality of the output individual trees, we performed data selection of the individual tree point clouds that best fit our research goals. We assessed the quality requirements for LiDAR data based on the principles outlined in the ISO 19157:2013 geographic data quality standard and evaluated the practicality of measuring branch growth by comparing QSMs from multiple time points.

In total, 294 tree point clouds were analyzed in this study, among which 166 trees were scanned using TLS in Evo, Finland, and 66 trees were scanned with PLS in Hyytiälä, Finland (Table 2). Additionally, 62 time-series point clouds were included, representing two individual

Table 2

Trees examined in this study. One point cloud per Time Series I and II is included in the table, representing the same tree for 32 birches and the same tree for 30 pines. This exclusion avoids redundancy, since these point clouds correspond to the exact same individual tree.

Method	Species	Trees	Mean ± SD DBH (cm)*	Mean ± SD height (m)*
TLS	Birch	23	9.00 ± 6.77	12.17 ± 7.15
	Pine	119	24.28 ± 3.64	17.40 ± 3.21
	Spruce	24	21.96 ± 4.03	14.36 ± 5.10
PLS	Birch	11	15.85 ± 4.81	19.05 ± 3.21
	Pine	42	22.74 ± 4.47	15.90 ± 5.27
	Spruce	13	—	—

* The DBH and height values were calculated only from realistic QSMs.

trees. Most trees from Evo (scanned using multi-view TLS) were Scots pines, with 24 spruces and 23 birches. We prioritized individual Scots pines with particularly simple branching structures, which reduced other sources of error and facilitated easier modeling. From Hyytiälä, 42 of the 66 trees were Scots pines, 11 were silver birches, and 13 were Norway spruces. For two individual trees, additional time points were modeled: 32 for one birch and 30 for one pine.

3.3. Processing pipeline II: from individual tree point clouds to QSMs

3.3.1. Wood and leaf separation

Accurate estimation of AGB using QSM requires the identification of woody structures in LS point clouds. Therefore, wood and leaf classification was applied to individual tree-level point clouds with leaves or needles. Only points classified as wood were used as input for QSM reconstruction.

For this task, we employed an unsupervised statistical approach adapted from Shcherbacheva et al. (2023), which enabled the automatic separation of foliage and wood by statistical fitting of scanner-measured intensity and geometric features, such as verticality and planarity. The foliage and wood classification method followed five key steps: 1) Feature extraction: Geometric features and LiDAR intensity values were extracted. Classification then began by applying an independent cross-scale saliency method, where each feature, including intensity, was evaluated independently to determine whether a point belongs to the wood or foliage class. 2) Model Fitting: A Gaussian Mixture Model (GMM) with two components, representing foliage and non-foliage, was fitted to selected geometric features and intensity values. 3) Inflection Point Identification: Inflection points were detected on the curve-fitted distributions of geometric attributes, particularly in the directions associated with the GMM clusters. 4) Segmentation: The point cloud was segmented using thresholds defined by the identified inflection points. Points were classified based on whether their feature values lie above or below the average of the two GMM component means. 5) Post-processing: Final refinement was done using Density-Based Spatial Clustering of Applications with Noise (DBSCAN), followed by the removal of both clustered and isolated noise (Shcherbacheva et al., 2023).

The calculation of geometric attributes was done by normalizing the eigenvalues λ_1 , λ_2 , and λ_3 of the 3D structure tensor, denoting them as e_1 , e_2 , and e_3 . The eigenvalues correspond to an orthogonal system of eigenvectors. Both the normalized and non-normalized eigenvalues were used in the calculations of the geometric attributes:

$$\text{Change of curvature } C_\lambda = \frac{e}{e_1 + e_2 + e_3} \quad (1)$$

$$\text{Linearity } L_\lambda = \frac{e_1 - e_2}{e_1} \quad (2)$$

$$\text{Anisotropy } A_\lambda = \frac{e_1 - e_3}{e_1} \quad (3)$$

$$\text{Sphericity } S_i = \frac{\lambda_3}{\lambda_1} \quad (4)$$

For the PLS data, regarding one time-point analysis, foliage and leaf classification was performed for 42 pines and 13 spruces (Table 2). Since all 11 PLS birches were scanned in early April without leaves, wood and leaf classification was not applied to deciduous tree point clouds. The wood and leaf separation was also done for the Time Series I and II point clouds, as mentioned in the Table 2 caption, although this did not include additional 18 birches that were scanned in leaf-off conditions. Therefore, leaves were removed from additional 30 pines and 14 birches. For the TLS data, additionally, we used the Adaptive Synthetic Sampling Algorithm (ADASYN) (He et al., 2008) for all trees scanned with TLS (Table 2), which generates synthetic samples inversely proportional to the density of the examples in the minority class, helping to address imbalances in classification tasks. This algorithm is particularly advantageous for QSM generation, as the initially separated wooden component often represents the underrepresented minority class. Shcherbacheva et al. (2023) reported an accuracy of 85 % for wood and leaf separation using the same TLS datasets.

3.3.2. QSM generation and visual evaluation

TreeQSM enables the automated generation of QSMs for individual trees, providing comprehensive representations of tree structure in which the geometries of stems and branches are fitted using hierarchical collections of cylinders. Nowadays, a range of QSM algorithms are available, such as AdTree, an adaptive tree reconstruction algorithm that builds skeletal models from point clouds (Du et al., 2019) and AdQSM, which refines QSM generation by improving the consistency and accuracy of tree volume and structural estimates (Fan et al., 2020). In our analysis, we used the TreeQSM v2.4.1 modeling tool (Raumonen et al., 2013; Raumonen and Åkerblom, 2024) implemented in Matlab (MathWorks, Massachusetts, USA), because of the accessible original scripts and the better understanding of the method.

TreeQSM requires minimally fragmented and leafless point cloud data for optimal QSM generation. It assumes that the input point cloud consists of points from a single tree. Along with the foliage and wood separation approach, TreeQSM's filtering method was applied to remove potential outliers and small components that may remain in segmented tree point clouds. This step ensured the accuracy and reliability of subsequent analyses. QSMs were generated for each tree often using the same optimized QSM reconstruction parameters across different time points. Three parameters should be optimized: 1) The first parameter is the patch size of the first uniform-size cover. The TreeQSM reconstruction method uses a cover set approach, where the point cloud is partitioned into small sets corresponding to local patches on the tree surface. These sets form the smallest units used to segment the point cloud into the trunk and individual branches. To improve and accelerate segmentation, the QSM reconstruction uses a two-iteration process. The segmentation is performed in two iterations. In the first iteration (first cover set), relatively large and uniform cover sets are used to remove non-tree points and capture the main branching structure. The second iteration (second cover set) then refines the segmentation with smaller, locally adjusted cover sets to better capture fine structural details. 2) The second parameter is the minimum patch size of the cover sets in the second cover. It is applied at the tips of the branches and the stem, and the value should be small enough to capture the tips of the branches. 3) The third parameter is the maximum cover set size at the base of the stem in the second cover. The value should be larger than the minimum patch size to avoid incorrect segmentation. Since we were working with the same tree at each time point, the initial parameters were optimized based on its unique structure and proved effective for generating reliable models throughout the dataset.

An important concern regarding the TreeQSM method is the robustness of the resulting QSMs. The method incorporates random elements, particularly in the cover set generation, which can lead to slight

variations in branch segmentation and the resulting QSMs with each modeling iteration. To assess the potential influence of these method-induced random changes when studying bi-temporal differences, we conducted robustness analyses of the QSM generation process using the first group of trees we analyzed. We prioritized this evaluation before including more trees in the analysis. It included evaluating the consistency of QSM metrics for an identical tree across multiple runs at the same time point. This initial evaluation served as a technical check to ensure that the TreeQSM algorithm produced stable results across all trees modeled at that time point. This assessment included 42 tree-level point clouds (11 pines, 18 birches, and 13 spruces) scanned with TLS, allowing us to evaluate TreeQSM's ability to maintain consistent metrics and provide reliable evidence for using QSMs in the temporal monitoring of tree structures. As the algorithm demonstrated complete reliability, QSMs were also generated for the rest of the tree point clouds, and their visual integrity was evaluated (Table 3).

An unsuccessful QSM generation in this context did not mean that the QSM script encountered an error, but that the resulting cylinder model failed to represent an intact tree when visually examining the three-dimensional QSM visualization. In these cases, the resulting visualization did not resemble an intact tree (Fig. 3), and the trunk model often failed to extend throughout the entire tree or included branches modeled separately from the rest of the tree structure. A realistic QSM was defined as one that lacks major visual inaccuracies, indicating that the model could represent the tree accurately. However, even visually intact models may not be perfect, as minor inaccuracies are inevitable, especially at the canopy top, where the original point cloud data were sparser compared to the bottom part of the tree (Fig. 3).

3.4. Branch-scale growth quantification

Direct pairing of individual branches between bi-temporal QSMs remained a challenging task. This complexity arised from changes in the QSM branching order, such as the loss or gain of branches between two time points. QSM branching order refers to the hierarchy of the branches in a QSM model, starting from the trunk. First-order branches grow directly from the trunk, while second-order branches grow from first-order branches. Third-order branches grow from second-order branches, and this pattern continues, with each higher-order branch growing from the one before it. Higher-order branches are typically smaller branches in the outer canopy, while lower-order branches are close to the trunk and are usually thicker. The alterations in the branch sequence complicated the creation of correspondence between branches at different temporal stages. As a result, the sequences of branches in the resulting branch-level data tables no longer remained identical (Fig. 4), making it difficult to compare branches across time points based on their index in the QSMs. This disruption negatively impacts the continuity and accuracy of assessing temporal changes in tree structures.

To address these challenges, we proposed a tree-level statistical comparison that included all branches. Rather than attempting a pairwise comparison of bi-temporal branch models, we opted for a more feasible method: evaluating overall structural consistency and investigating the trends in bi-temporal branch growth. We generated frequency graphs using Python self-developed scripts that illustrate the tree-level

Table 3

Success rate of visually intact QSM generation. One point cloud per time-series is included in the table, representing the same tree for 32 birches and the same tree for 30 pines.

Method	Species	Realistic QSMs	Total QSMs	Success rate (%)
TLS	Birch	3	23	13.04
	Pine	73	119	61.34
	Spruce	4	24	16.67
PLS	Birch	7	11	63.64
	Pine	8	42	19.05
	Spruce	0	13	0

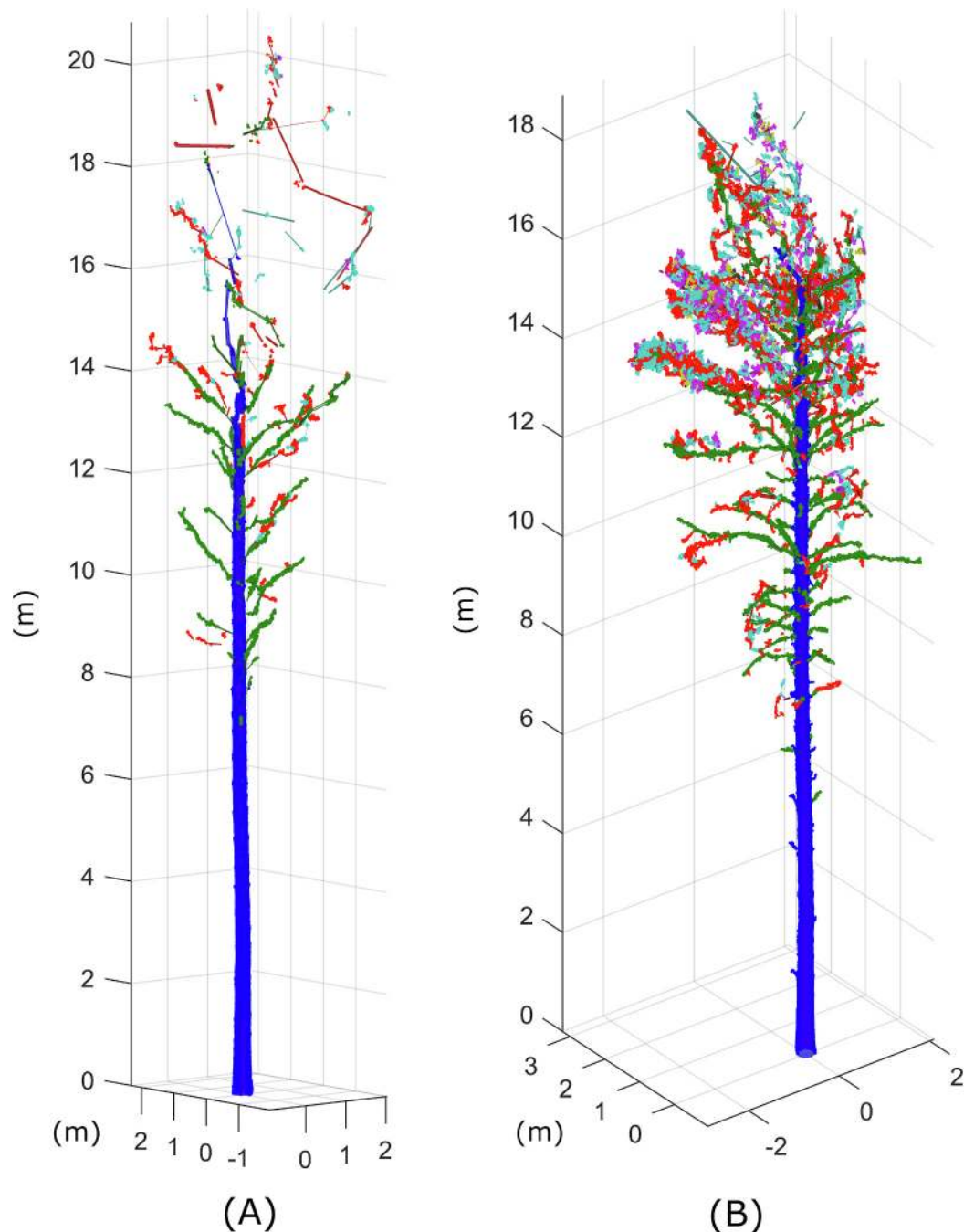


Fig. 3. The difference between A – an unrealistic QSM and B – a visually intact QSM with minor inaccuracies, particularly in the canopy section. Both pine trees were scanned with TLS in Evo, Finland. Blue represents the trunk (order 0), green indicates order 1 branches, red indicates order 2, turquoise indicates order 3, purple indicates order 4, yellow indicates order 5, and black indicates order 6. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

statistical distribution of nine QSM metrics for individual Scots pine trees scanned with PLS. We selected these individual trees because of their simple branch architecture compared to species Norway spruce and silver birch, which typically exhibit more complex branching structures.

We studied nine QSM metrics that include branch diameter (m), branch height (m), branching order, branch area (m^2), branch angle (degrees), branch zenith angle (degrees), branch azimuth angle (degrees), branch length (m), and branch volume (L). These metrics provide a comprehensive geometric characterization of branching structures. Additionally, we generated frequency graphs for the TLS data, showing the distribution of the same nine tree-level QSM metrics for nine pine

trees. Tree selection was based on the visual integrity of the QSMs. In other cases, one or both time points lacked a visually intact QSM, making them unsuitable for reliable bi-temporal comparison.

3.5. Experiment design and assessments

3.5.1. Experiment I – Feasibility of branch level tree growth study using QSMs

In this experiment, the overall feasibility of using different LS systems for quantitatively assessing tree growth at the branch level through multi-temporal QSMs was evaluated. This involved, firstly, analyzing the robustness and the success rate of the applied QSM generation

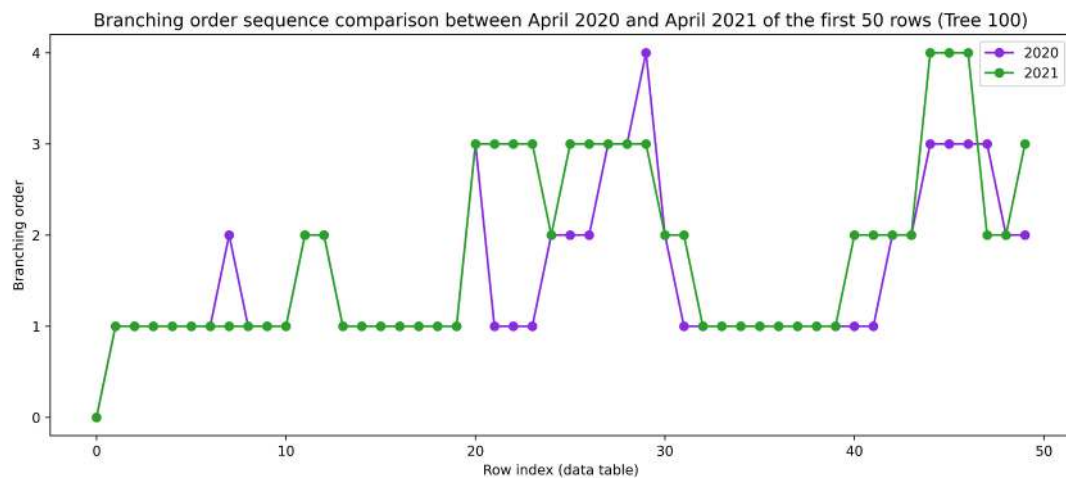


Fig. 4. The difference between the QSM branching order sequences of the first 50 rows (0–49) in the branch-level data table between April 2020 and April 2021 for a pine tree scanned with PLS. The branch-level data tables include QSM metrics for individual branches. QSMs from different time points typically exhibit this kind of misalignment, making it difficult to match all corresponding branches based on their index (row) across the data tables.

approach while using different LS datasets and for different species. As a preliminary assessment, the TreeQSMs were visually inspected to determine if the generated QSMs were realistic and intact. For example, we manually inspected whether a trunk was accurately modeled at the canopy section and whether the branches were properly attached to the tree structure. As a second step, datasets from an additional time point were included to investigate the success rate for deriving reliable QSMs for an identical tree using dataset collected at different times, thus, to evaluate the feasibility of different LS systems in carrying out branch-level dynamic studies for different species.

3.5.2. Experiment II – Validation with field measurements

Visually verified QSM models (Table 3) were validated with respect to field measurements to further evaluate their accuracy. This included 52 trees scanned with TLS, i.e., 3 birches, 46 pines, and 3 spruces, and 10 trees scanned with PLS, i.e., 5 birches and 5 pines, for which visually inspected QSMs were successfully generated using bi-temporal datasets (Table 3). For the TLS data, field references (unpublished, produced by the Center of Excellence in Laser Scanning, 2014) were collected in 2014 at the same time as the 2014 TLS data acquisition. For the field reference, the diameter at breast height (DBH) was measured using a tree caliper, and the tree height was measured using a Haglöf Vertex tree height meter in the field. When the field reference was not available for certain trees, the tree heights were estimated from the point clouds. For each tree, the ground height was derived from the nearest point to the stem bottom on a 20-cm digital terrain model (DTM), and the tree's top height was defined as the 99.95th percentile of its vertical (H) coordinates (Tompalski et al., 2021). Similar approach was implemented for acquiring reference tree height information for trees covered by PLS, where Yrttimaa et al. (2024) evaluated the variability of height estimates using different height percentiles in PLS point clouds, while Campos et al. (2024) evaluated the consistency of the height estimation with the PLS point cloud, finding a mean variation of less than 5 cm. For the PLS-scanned trees, DBH measurements were available for only 40 % of the successful QSMs, where the DBHs were either manually measured or measured with a dendrometer.

For trees in the TLS dataset, the validation was performed only for QSM models generated using the 2014 dataset, where the field reference was collected in the same year as the TLS data. No field reference data were collected in 2019. For the PLS trees, the validation was performed only for those trees for which reference data were available, i.e., the measurements were taken within a three-month period of the point cloud collection.

The reference values that were calculated included the mean

absolute error (MAE), mean percentage error (MPE), and root mean square error (RMSE). MAE measures the average absolute difference between the predicted values and the actual values without squaring, while MPE measures, on average, how far off the predictions are in percentage terms. It also indicates whether there is overprediction or underprediction. RMSE, on the other hand, measures the square root of the mean of squared prediction errors and is sensitive to large deviations.

These reference values were compared with the corresponding QSM-derived metrics to provide a benchmark for the reliability of QSM-derived basic tree metrics. A success threshold was defined based on the accuracy of height and DBH measurements to further assess the reliability of QSMs. QSMs were considered successful if they produced height estimates with a MAE of less than 1 m and DBH estimates with an MAE of less than 2 cm. These thresholds were chosen to reflect practical tolerances for structural realism in the absence of full field-based structural validation. Each validated QSM was evaluated against these criteria, and success rates were calculated separately for height, DBH, and for QSMs that met both. Due to the limited availability of field-measured DBH for PLS trees, success rates based on DBH for PLS birch and pine are based on only two trees per species and are indicative rather than conclusive.

However, it is important to note that while DBH and height are critical parameters, their accuracy does not fully guarantee the reliability of the QSMs that reflect the full structural details of trees, especially when the QSM tree structure appears distorted or incomplete.

3.5.3. Experiment III – Investigating the boundary conditions for QSM generation

We conducted a thorough selection of individual tree point clouds to analyze the LS data requirements for branch-level change detection. In this context, LS data requirements refer to the necessary data quality needed to reliably detect structural branch-level changes. The segmented tree point clouds exhibit varying densities and levels of completeness, which are inherent to both the LS data acquisition process and the preprocessing framework applied to the data. Given these variations, we analyzed individual tree point clouds based on different species, spatial resolutions, and levels of completeness. To evaluate whether the point clouds met these requirements, we applied specific assessment metrics, including tree representation accuracy (assessed through spatial resolution), completeness (considering both omission and commission errors), logical consistency, temporal quality, and usability, following the ISO 19157:2013 standard.

To analyze the effect of spatial resolution on QSM estimation, we

selected a birch tree with a particularly high spatial resolution and completeness from the PLS dataset. We considered this tree a good representative of a best-case scenario and an ideal reference for assessing how spatial resolution impacts QSM outcomes. Therefore, the observed effects reflect the lower limit of deterioration that this analysis was intended to reveal. We then resampled the individual tree point cloud using a voxelization-based process with cubic voxel sizes of 2 cm, 5 cm, 10 cm, 15 cm, and 20 cm. The resampling process was carried out using a KD-tree-based neighborhood search method, where the real point closest to the centroid of all points in each voxel was preserved. The QSMs were initially generated using standard QSM reconstruction parameters. In cases where unrealistic modeling results were obtained, we optimized the parameters to improve accuracy and to evaluate the extent to which parameter adjustment could compensate for reduced QSM quality.

Point cloud completeness was assessed by considering its two sub-elements: omission (absence) and commission (excess). Omission errors occur due to occlusions during data acquisition, such as missing parts of the tree due to the scanning geometry or low resolution. In this study, omission refers to tree point clouds where parts of the structure are missing due to the data acquisition geometry or low resolution, for instance, parts of the canopy or stem missing. Commission errors, on the other hand, are caused by poor tree segmentation, atmospheric particles, moving objects, and instrumental noise, resulting in extra points that do not belong to the tree structure.

Omission errors were analyzed by creating volumetric point density profile figures for individual trees using Python self-developed scripts. These profiles were generated for four pine trees and four birches (two per each dataset: PLS and TLS), as well as for two spruces scanned with TLS. Only two per dataset were selected to provide clear examples illustrating the variety in the data. The profiles highlight differences in point density between tree point clouds with visually intact and visually incomplete QSM reconstructions. Volumetric point density (points/m³) was calculated using vertical slices of 0.1 m in height and the full horizontal extent of the point cloud. Each slice's volume was calculated by multiplying its ground area by the slice height, allowing us to create smoothed vertical point density profile curve for each tree point cloud. Additionally, two visual examples were created to demonstrate the effects of omission: one showing how the fixed scanning perspective of the PLS station affects the completeness of the tree trunks. Mean point density per cubic meter was calculated for all QSMs from both PLS and TLS datasets. Logistic regression analysis was used to assess the relationship between mean point density and visual QSM integrity. Similarly, we also analyzed mean distance from the scanner to the input point cloud for the whole PLS dataset, which exhibits significant variability in distances. The measurements can range up to 200 m.

For commission errors, we simulated three types of noise around the same birch tree scanned with PLS, selected for analyzing spatial resolution, to evaluate their effects on QSM quality. The first type involved random points scattered around the tree in six cases: 500, 1000, 2000, 3000, 4000, and 5000 points. The second type consisted of spherical clusters of points with varying point densities and 3D radii, ranging from 1500 to 9500 points in increments of 1000 points, for a branch simulation radius of 0.1, 0.5, and 1 m. This simulation aimed to assess how QSM generation and parameterization respond to sparse and clustered noise. The third type of noise involved a point cloud cluster created to simulate an extra branch, such as one from a neighboring tree that was not properly segmented.

The temporal quality of the datasets was evaluated by examining changes in nine tree-level QSM metrics: branch volume, branch length, number of branches, branch order, branch area, DBH, average crown diameter, crown area, and crown volume. These metrics were selected to represent both branches and the crown, with DBH included to track changes in trunk size over time. Line graphs were created for one birch tree and one pine tree, both scanned with PLS. The birch time series (Time Series I) spanned from May 2020 to September 2021 with 32 time

points (two per month), while the pine time series (Time Series II) covered April 2020 to July 2021, with 30 time points.

The geometric logical consistency of the point cloud data was integrated into the analysis of other data requirements, including spatial resolution and omission. In these analyses, the effect of point density on logical consistency was explored, particularly in relation to the resulting QSM structures. Additionally, the impact of artificial noise on the logical consistency of QSMs was analyzed as part of the commission analysis. Results related to spatial resolution, completeness, temporal resolution, and logical consistency are presented in [Section 4](#).

3.5.4. Experiment IV – What can be learned about tree branch growth from multi-temporal QSMs

The ultimate objective of inspecting the feasibility and reliability of generating multi-temporal QSMs for trees is to explore the potential for investigating tree growth strategies, i.e., how each tree allocates its growth and how the growth allocation is affected by the tree itself and the local biotic and abiotic factors. This experiment demonstrates the varied growth strategies of different individual pine trees over a five-year span, which can be quantitatively assessed and modeled using multi-temporal QSMs.

4. Results

The results are presented in this section, corresponding to the key research questions and aligned with the experiments.

4.1. Success rate of visually intact QSM generation

[Table 3](#) summarizes the success rates of visually intact QSM generation for birch, pine, and spruce trees across the two point cloud acquisition methods—PLS and TLS—at two different time points. It is important to note that this evaluation is initial, and field validation was performed later to further assess model accuracy. The data reveal variability in success rates depending on species and acquisition method. For birches, the TLS method achieved only a 13.04 % success rate, while PLS demonstrated a substantially higher success rate of 63.64 %. For pines, the highest success rate was observed with TLS at 61.34 %, compared to just 19.05 % with PLS. Spruces proved to be the most challenging species for visually intact QSM generation, with a success rate of only 16.67 % for TLS and 0 % for PLS.

Various factors contribute to the generation of unrealistic QSMs. One of the most common issues is inaccurate individual tree segmentation, where the tree structure is disrupted by intertwined branches from neighboring trees or nearby undergrowth that was not fully removed. Another frequent cause is a sparse or fragmented point cloud. Unrealistic QSM generation can also be influenced by species-specific or data-specific issues. For instance, in the PLS data, tree point clouds were often patchy, with large sections entirely missing. In such cases, points representing woody structures were poorly connected, causing the QSM algorithm to make approximations that may not accurately reflect the actual tree structure.

4.2. Field validation of the visually intact QSMs

TLS-based, visually intact QSMs generally showed high accuracy across the three tree species, particularly for DBH estimates ([Table 4](#)). Mean absolute error (MAE) in DBH was lowest for birch (0.06 cm), followed by pine (0.67 cm) and spruce (1.04 cm), with corresponding RMSE values below 1.2 cm for all species. The MPE errors for DBH were consistently low and slightly negative, indicating minor underestimation. Height estimates varied more. Birch showed the best performance (MAE = 0.53 m, RMSE = 1.09 m), while spruce exhibited the highest errors (MAE = 11.54 m, RMSE = 11.80 m), suggesting limitations in accurately capturing the treetops of tall conifers.

PLS-based models demonstrated moderate accuracy, with more

Table 4

Field validation results of the intact QSMs. All trees were fully grown with a mean height of 20.62 m.

Scanning method	Tree species	MAE, DBH (cm)	MPE, DBH (%)	RMSE, DBH (cm)	DBH-measured trees	MAE, height (m)	MPE, height (%)	RMSE, height (m)	Height-measured trees
PLS	Birch	1.65	11.36	2.33	2	0.05	-0.27	0.12	5
PLS	Pine	1.16	5.90	1.66	2	6.10	-32.70	6.90	5
TLS	Birch	0.06	-2.53	0.30	3	0.53	-1.60	1.09	3
TLS	Pine	0.67	-2.50	1.09	46	3.74	-17.60	4.53	46
TLS	Spruce	1.04	-4.16	1.18	3	11.54	-48.74	11.80	3

varying performance across tree species (Table 4). DBH estimates were more accurate for pine (MAE = 1.16 cm, RMSE = 1.66 cm) compared to birch (MAE = 1.65 cm, RMSE = 2.33 cm), suggesting species effects in stem diameter estimation. Height estimation was notably less reliable with PLS, especially for pine, where the mean absolute error reached 6.10 m and mean percentage error was -32.70 %. Birch height errors were minimal (MAE = 0.05 m, RMSE = 0.12 m).

The comparison of QSM success rates across methods and species showed clear variation in model performance (Table 5). For TLS, birch had the highest proportion of models meeting both the height and DBH error thresholds, with 66.7 % of validated QSMs considered realistic. Pine had a high number of validated QSMs ($n = 46$), but only 3.4 % met both criteria, reflecting a lower success rate despite the larger sample. Spruce had no models fulfilling both thresholds. In contrast, PLS-derived QSMs for birch showed a 100 % success rate for height and 40 % for DBH, with 40 % meeting both criteria based on a small validation sample ($n = 5$) with only two DBH measurements available. For PLS pine, only 20 % of the QSMs met the height criterion and 40 % the DBH threshold, while none fulfilled both simultaneously. Again, only two trees had DBH data.

4.3. Boundary conditions for reliable multi-temporal QSM generation for three main boreal species

4.3.1. LS positional accuracy and spatial resolution

Successful QSM generation and growth detection depend on accurately identifying and matching individual trees and branches. This requires topological tree representations to be precise, complete, and logically consistent. The spatial resolution of the point cloud is crucial in ensuring accurate tree representation for QSM modeling, particularly for detecting changes at the branch level.

Point distance significantly affects QSM quality (Fig. 5 and Fig. 6). A uniform point distance of 2 cm seemed to typically produce realistic models, representing the lower limit of deterioration in QSM quality. However, a point distance of 5 cm did already result in unrealistic QSMs, even with optimized TreeQSM reconstruction parameters and ideal QSM quality (Fig. 5). At a 10 cm point distance, the models became increasingly unrealistic and at 15 cm or 20 cm, the models barely resembled trees. Optimizing QSM reconstruction parameters mitigated unrealistic modeling for point clouds with a 5 cm point distance, particularly for trunks and main branches. However, with point distances of 10 cm or greater, models became less structurally complete, and at 20 cm, only the trunk remained.

Table 5

Success rate of realistic QSM generation.

Method	Species	QSMs with height MAE < 1 m and DBH MAE < 2 cm	QSMs with height MAE < 1 m	QSMs with DBH MAE < 2 cm	Total validated QSMs	Realistic height + DBH success rate (%)	Realistic height success rate (%)	Realistic DBH success rate (%)
TLS	Birch	2	2	3	3	66.67	66.67	100
	Pine	4	4	44	46	3.36	3.36	95.65
	Spruce	0	0	3	3	0	0	100
PLS	Birch	2*	5	2*	5	40*	100	40*
	Pine	0*	1	2*	5	0*	20	40*

* Only 2 trees had DBH measurements.

4.3.2. Temporal accuracy

Figures 7 and 8 show the temporal changes in nine QSM metrics from May 2020 to September 2021 for individual birch and pine trees scanned with PLS. Branch-related metrics exhibited slight growth during this period, suggesting overall branch growth.

Although DBH values exhibited some variability, the QSM time series maintained a general consistency. However, foliage removal algorithms significantly reduced branch volume, total combined branch length, number of branches, branch area, and crown volume during the summer. Maximum branch order was also affected, while average crown diameter and crown area were less impacted. These reductions likely result from the algorithm removing points belonging to woody structures, particularly from smaller branches, as indicated by changes in maximum branch order. For pine trees, distorted values during the winter (Fig. 8) were attributed to heavy snowfall on branches.

4.3.3. Point cloud completeness

Realistic QSMs were generated when the local point density remains consistent throughout the entire tree structure (Fig. 9 and Fig. 10). Unrealistic models often resulted from sparsely populated or missing sections in the point clouds. While high local point densities (e.g., 10,000 points/m³) were not strictly necessary, a minimum local density of 500 points/m³ seemed to be critical for creating realistic QSMs, especially when the point cloud uniformity was imperfect.

However, Fig. 11 suggests that while mean point cloud level volumetric point density was a statistically significant predictor of visual QSM success ($p = 0.001$), its effect was very small and slightly negative (coefficient = -0.0002), indicating that higher mean point density had minimal and somewhat detrimental impact on QSM outcomes. This variable alone explained only a small portion of the variability in model outcomes (pseudo $R^2 = 0.087$). Additionally, the presence of branches from neighboring trees introduced structural noise (Fig. 9e), leading to unrealistic QSMs.

The fixed scanning perspective in PLS data significantly affects QSM quality, particularly because the scanner's field of view failed to capture the entire tree structure. As shown in Fig. 12, this limitation led to incomplete trunk and crown shapes. The side of the tree facing away from the scanner was poorly represented or entirely absent in the point cloud, resulting in gaps and semi-circular trunk shapes.

Noise in the point cloud also distorted QSM results, particularly when noise clusters resemble branches and the default TreeQSM filtering parameters were used. These parameters are designed to handle a wide range of tree structures effectively, but adjustments may be required for specific cases or higher precision needs. In particular,

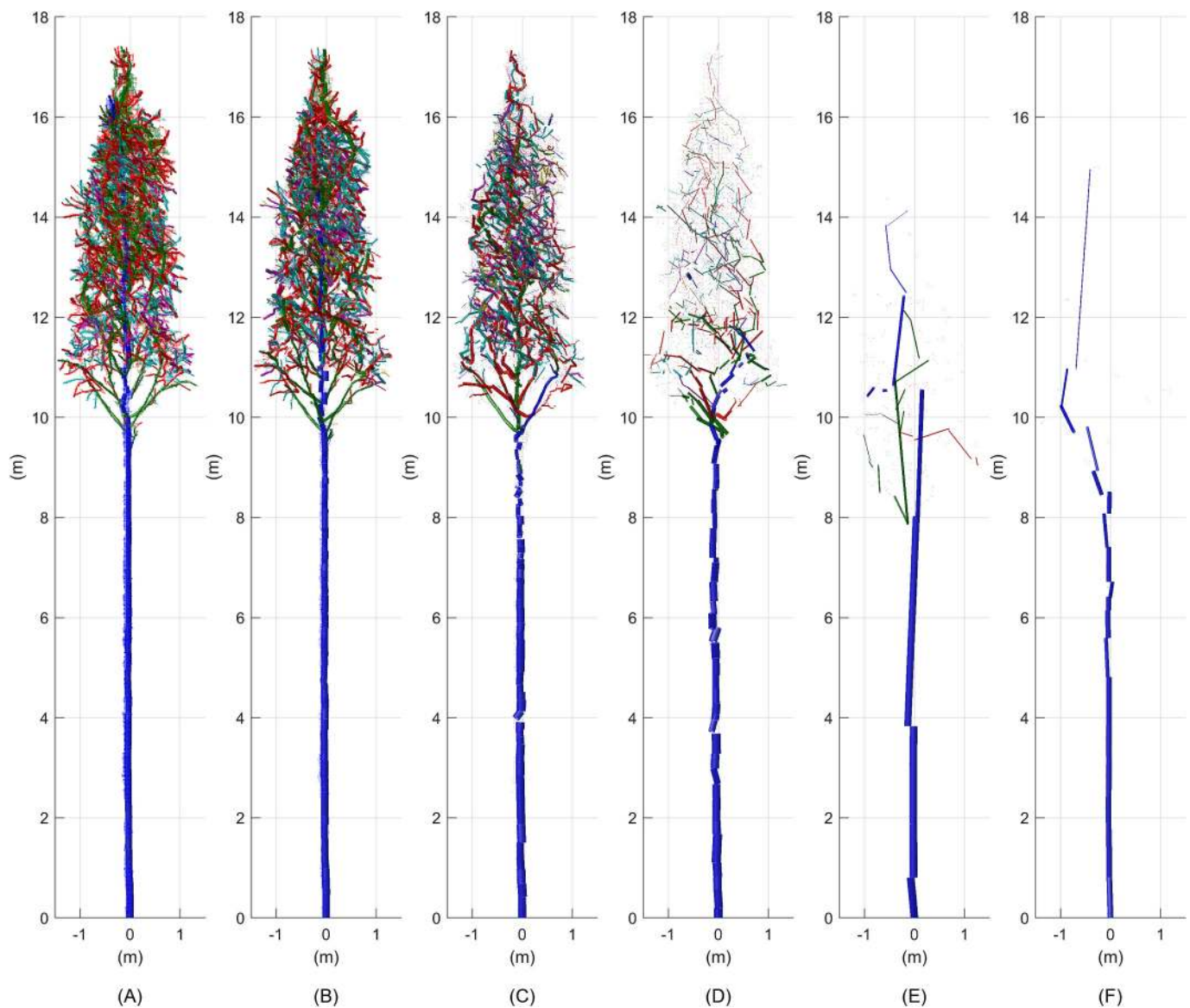


Fig. 5. The effect of resampling the point cloud on visual QSM integrity when using the same reconstruction parameters for all cases. A single birch tree (tree 805) is shown. The tree was scanned in April, meaning that there were no leaves in the original point cloud. The point cloud was scanned with PLS. From left to right: A – the original point cloud, B – 2 cm point distance, C – 5 cm, D – 10 cm, E – 15 cm, and F – 20 cm. The QSM reconstruction parameters were optimized for the original point cloud.

spherical noise clusters with higher point densities skewed results as the radius increases. For instance, a sphere with a radius of 1 m and 9500 points produced a significantly different result from one with only 2500 points at the same radius (Fig. 13). Such noise typically inflated the estimated branch volume, as the noise clusters were mistakenly modeled as additional branches. Random individual points scattered around the tree, even in quantities as high as 5000, seldom affected the QSM. However, if noise was incorporated into the final model, it appeared as additional branches that are either attached to the tree or completely detached, particularly if the noise cluster was located farther away from the trunk.

Figure 14 presents the relationship between the mean distance to the scanner and visual QSM success using logistic regression. The results showed a weak negative association, with trees located farther from the scanner, tending to have a lower probability of successful QSM generation. However, the effect of mean scanner distance was not statistically significant ($p = 0.119$), and the explanatory power of the model remained modest (pseudo $R^2 = 0.055$). While the full model was

marginally significant based on the likelihood ratio test ($LLR p = 0.048$), the wide confidence interval for the distance coefficient (-0.030 to 0.003) suggests caution in interpreting this trend.

4.4. Feasibility of tree-wise growth strategy study from bi-temporal QSM statistical analysis

Once multi-temporal (at least bi-temporal) QSMs were successfully generated and co-registered, analyzing branch-level growth dynamics of different trees using statistical comparisons became feasible, even though directly pairing branches across time points remained challenging. Fig. 15 presents frequency graphs of tree-level QSM metrics for the branches of a single Scots pine tree scanned in April 2020 and 2021 using PLS in Hyytiälä, Finland. The graphs show slight variations across all tree-level QSM branch metrics, with noticeable reductions in larger, lower-order branches. In contrast, higher-order branches exhibited slight increases, indicating some growth in the outer canopy. Overall, the distributions of branch diameter, height, area, length, and volume

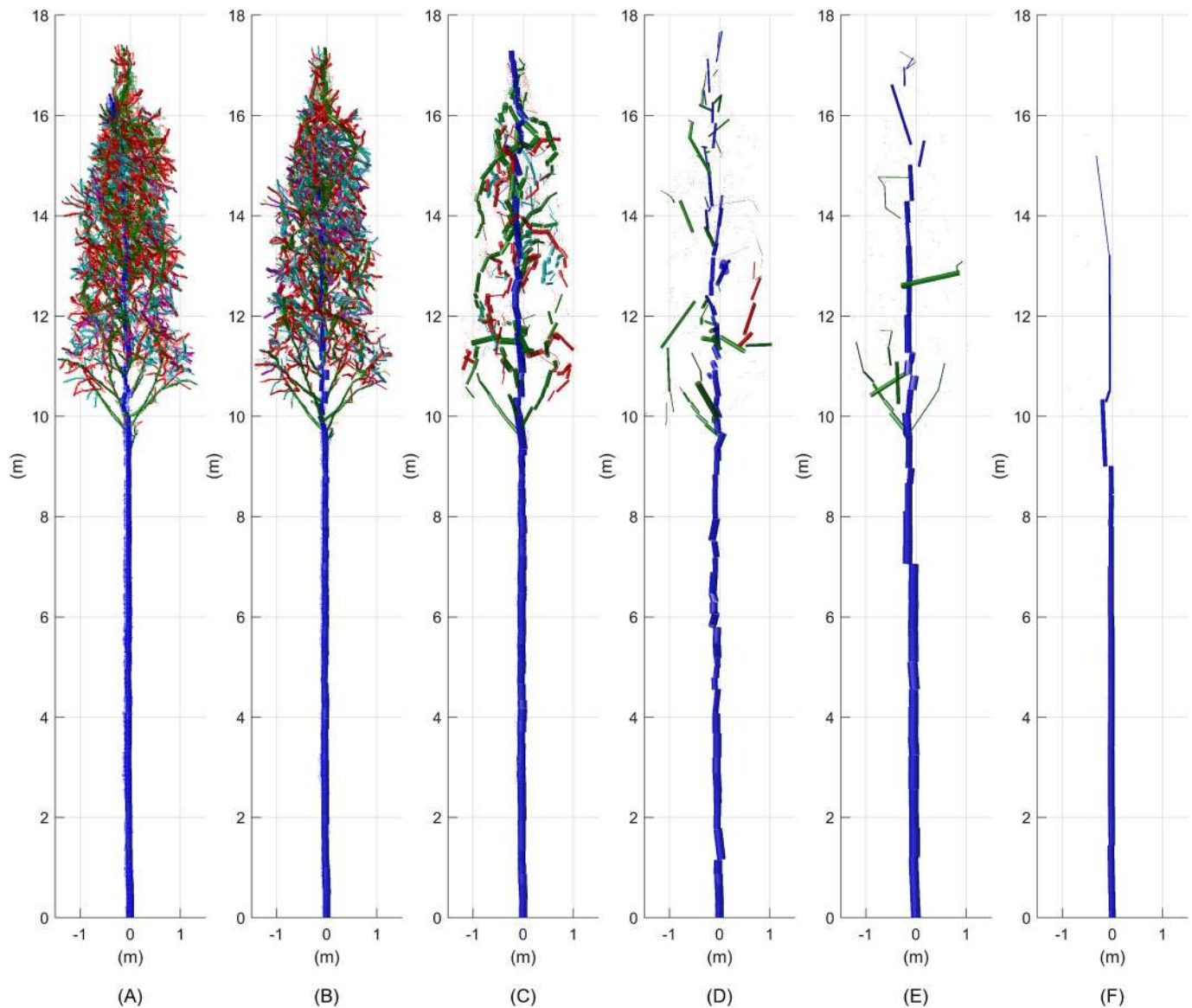


Fig. 6. The effect of resampling the point cloud on visual QSM integrity when using optimized reconstruction parameters. The same data were used as in Fig. 4. From left to right: A – the original point cloud, B – 2 cm point distance, C – 5 cm, D – 10 cm, E – 15 cm, and F – 20 cm. The latter four point distances were optimized. Each point distance was modeled with its own adjusted QSM reconstruction parameters to showcase how optimization can mitigate point cloud sparsity by aiming to preserve the main structure of the tree, especially the trunk.

remained relatively stable between the two time points, suggesting minimal structural changes but some development in finer branching levels.

Figures 16 and 17 show frequency graphs of branch metrics for Scots pine trees scanned with TLS in Evo, Finland, in 2014 and 2019. These figures highlight differences in branch growth over the five-year period, reflecting the dynamic nature of forest ecosystems. Even within the same species, growth patterns varied. For example, Fig. 16 shows a notable increase in branch height and the number of branches, indicating growth in the upper canopy, alongside a reduction in larger branches. Meanwhile, Fig. 17 reveals a decrease in the number of smaller branches, while higher-order branches remain stable or slightly increase, suggesting branch shedding in some sections.

The TLS approach appears particularly reliable for capturing larger branches (Fig. 18), likely due to its dense coverage and higher spatial resolution. However, noticeable declines in QSM quality were observed in the uppermost sections of tree canopies, reducing model accuracy and completeness. These issues may stem from challenges in data fusion and

alignment, particularly in regions with dense foliage or complex branching structures.

5. Discussion

Previous studies have made significant progress in estimating AGB at the individual tree level through the integration of TLS + QSM approaches (Calders et al., 2015; de Tanago et al., 2017; Lau et al., 2018). In contrast, our investigation represents a shift from the conventional focus of earlier research toward the prerequisites for studying branch-level growth dynamics.

Ensuring reproducibility by minimizing changes unrelated to temporal variations is a fundamental prerequisite for conducting temporal studies using QSM. We have confirmed reproducibility through our verification process by ensuring the consistency of QSM metrics for a single time point. This is demonstrated by the identical results for branch metrics from consecutive runs, when restarting Matlab between the runs due to the random elements in the reconstruction process. Our

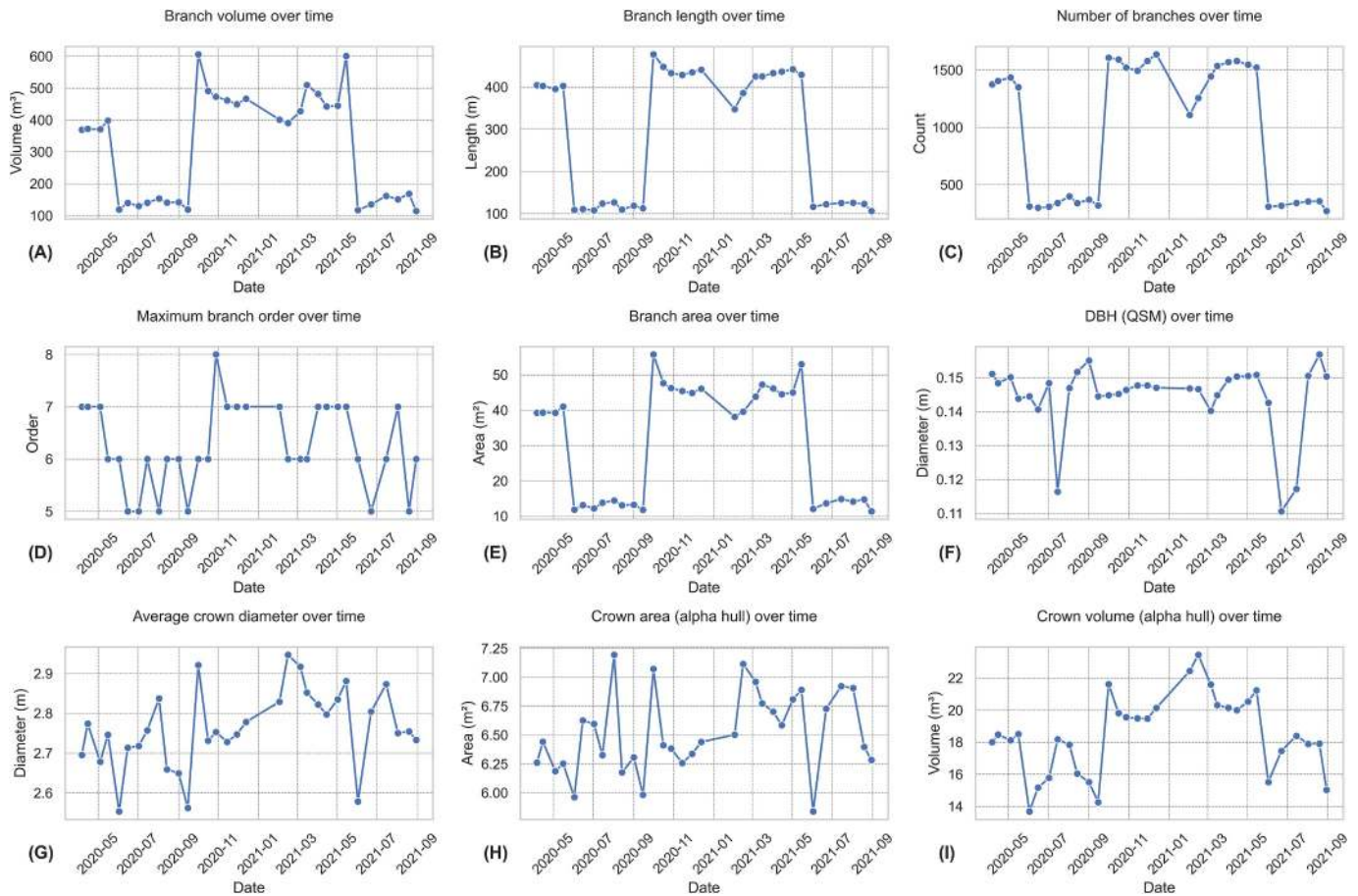


Fig. 7. Time Series I from May 2020 to September 2021 showing the temporal change in nine QSM metrics for a birch tree (tree 805) scanned with PLS.

evaluation confirms the basic utility of QSMs for studying temporal changes in tree structure. The modeling method can consistently produce reliable metrics across multiple trees from different species.

5.1. Influence of point cloud quality and processing strategies on QSM accuracy

Point cloud spatial resolution significantly influences QSM quality and logical consistency (Raumonen and Åkerblom, 2024). While absolute positional accuracy of the LS point cloud is less critical, effective QSM modeling is strongly impacted by point spacing, which affects the accurate representation of trees. However, our logistic regression analysis revealed a statistically significant but practically negligible negative effect of mean volumetric point density on the likelihood of generating a visually successful QSM (coefficient = -0.0002, $p = 0.001$). The relatively low explanatory power of the model (pseudo $R^2 = 0.087$) indicates that point density alone cannot explain QSM success or failure. It should be noted that, although mean distance to the scanner is a critical factor influencing the point density, it showed a weaker relationship ($p = 0.119$) with the success rate of QSM generation than point density. This suggests that point density is a result of multiple impact factors, including forest stand conditions and the viewing geometry, as well as structural noise from neighboring branches. Therefore, a high mean volumetric point density does not necessarily reflect an ideal point cloud for QSM.

Nevertheless, reliable QSM generation still required the point density to exceed a certain threshold across the entire tree. A realistic QSM was achievable with a minimum local volumetric point density of approximately 500 points per cubic meter with a vertical extent of 0.1 m when point cloud uniformity was imperfect. Uniform point distances

exceeding 5 cm appear to have resulted in increasingly oversimplified and unrealistic models, even with optimized QSM reconstruction parameters and otherwise ideal QSM quality. Conversely, a uniform point distance of 2 cm was shown to produce realistic QSMs (e.g., Yazdi et al., 2024).

Input point clouds must strictly include an entire single tree without overlapping points from nearby trees or shrubs, as emphasized in the TreeQSM official documentation (Raumonen and Åkerblom, 2024). Ideally, the uppermost sections of the tree canopy should be included, and the point cloud should not contain noticeable gaps. Realistic models generally exhibited maximum intact-section gaps of around 20 cm, while larger gaps (e.g., 30–100 cm) were common in fragmented point clouds, leading to unrealistic models with erroneous QSM metrics, such as incorrect branch lengths and diameters.

Noise in LS point clouds also affects QSM accuracy and logical consistency. The official TreeQSM documentation suggests that it is ideal to avoid using point clouds with significant noise since additional points can be mistakenly modeled as branch structures (Raumonen and Åkerblom, 2024). While random individual points rarely appeared in the final model, noise clusters resembling branches were often modeled as additional branches, sometimes even detached from the main tree structure. Careful segmentation was therefore essential to exclude branches or bushes that did not belong to the tree. Spherical noise clusters were also sometimes interpreted as additional branches in the final QSM, distorting the resulting metrics. When simulating noise, the density and spread of points within a given radius influenced how the noise was interpreted by the algorithm. Larger, denser clusters were more likely to be misidentified as branches as their radius increased. For example, clusters with 9500 points in a 1-m radius tended to produce higher total branch volumes compared to clusters with 2500 points at

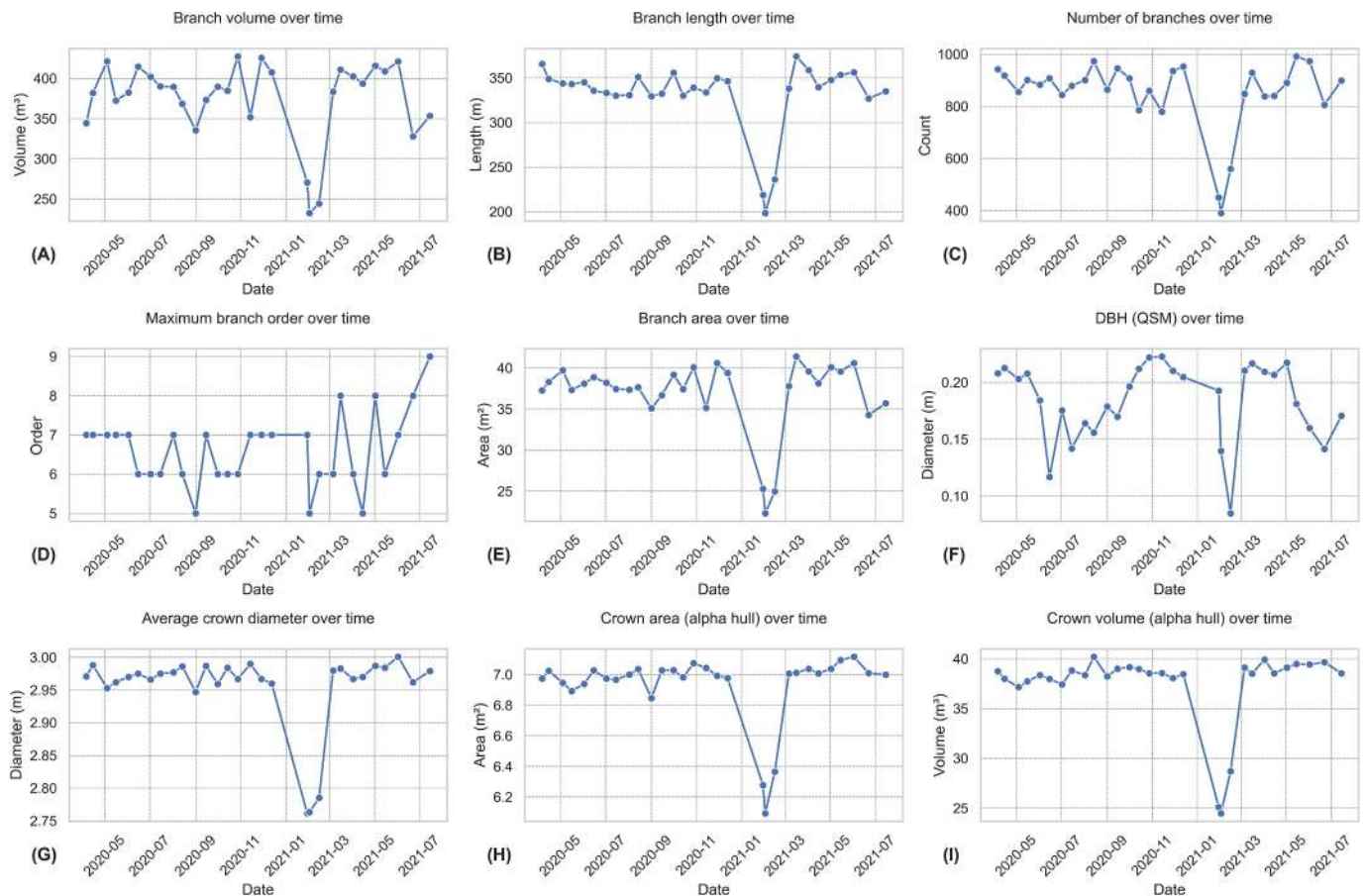


Fig. 8. Time Series II from April 2020 to July 2021 showing the temporal change in nine QSM metrics for a pine tree (tree 239) scanned with PLS.

the same radius. This trend was particularly evident for larger radii (e.g., 0.5-m and 1.0-m radii), where increasing point counts progressively resulted in higher branch volume estimates. In contrast, smaller radii of 0.1 m showed less sensitivity to point density, with branch volumes remaining relatively stable.

A very precise foliage-wood removal process is crucial for realistic QSM generation. This step is considered one of the most challenging in LS processing for QSM modeling, due to the inherent heterogeneity and complexity of trees, and it often requires substantial training or significant parameterization. As such, leaf and wood separation remains an ongoing challenge and active area of research in the LS community (Ali et al., 2024). Several supervised (Ma et al., 2016; Wang et al., 2017; Zhu et al., 2018; Moorthy et al., 2020; Xi et al., 2020) and unsupervised (Tao et al., 2015; Ferrara et al., 2018; Vicari et al., 2019; Wang et al., 2020; Hui et al., 2021) methods for this task have been developed and can be considered depending on the forest data being used. Removing the needles, in particular, is especially challenging and should be done carefully. Otherwise, the cylinders may not properly represent the dimensions of the woody parts of the tree. Foliage-wood separation algorithms often mistakenly remove points that belong to woody material, leading to a reduction in the QSM metrics during the foliage season. This issue primarily affects the smallest branches. Additionally, the presence of leaves increases occlusion within the tree crown (Calders et al., 2015). As expected, the temporal analysis of QSM metrics from May 2020 to September 2021 suggested that the most accurate results were obtained when temporal analyses were conducted in leaf-off seasons.

Branch structure complexity significantly influences QSM quality and varies among tree species. Hui et al. (2021) and Torresan et al. (2018) highlight the persistent challenge of obtaining precise branch information from TLS data, particularly with coniferous trees. We found

that trees with more complex branching structures, such as spruces, tended to result in less accurate QSMs. Birch trees typically have slender trunks and fewer, less complex branches, which may simplify the modeling and result in higher accuracy when QSMs are successfully generated. Birches can be scanned in leaf-off conditions, which enhances the visibility of woody components. This visibility may have a greater impact on QSM reconstruction accuracy than structural differences between tree species. Nevertheless, previous studies have shown that the modeling accuracy of QSM-derived volumes decreases with complex branch structures (Torresan et al., 2018; Brede et al., 2019). Norway spruce has a layered and dense branching pattern with numerous small twigs, which seems to complicate QSM reconstruction. Scots pine has thicker and more regularly spaced branches and a more open crown structure, making it easier to model despite also retaining its needles. Intricate patterns with numerous small branches often resulted in inaccurate and uncertain models, while larger lower branches appeared to contribute to more reliable models. Several other studies also support this finding (Hackenberg et al., 2014; Kaasalainen et al., 2014; Hackenberg et al., 2015; de Tanago et al., 2018; Qi et al., 2022).

Our study enhances the understanding of the distinct advantages and disadvantages of PLS and TLS. The fixed sensor-target alignment of PLS remained consistent across various time points, making tree point clouds statistically comparable and suitable for longitudinal studies and temporal analyses. However, the specific characteristics of PLS data posed challenges for QSM generation, including noise, fragmentations, and distortions. Additionally, the fixed scanning geometry limited the visibility of complete tree structures (Liang et al., 2016; Wittke et al., 2024), with partial tree segments leading to inaccurate QSMs. While greater distances from the scanner may contribute to reduced modeling accuracy, scanner distance alone was not a reliable predictor of visual QSM

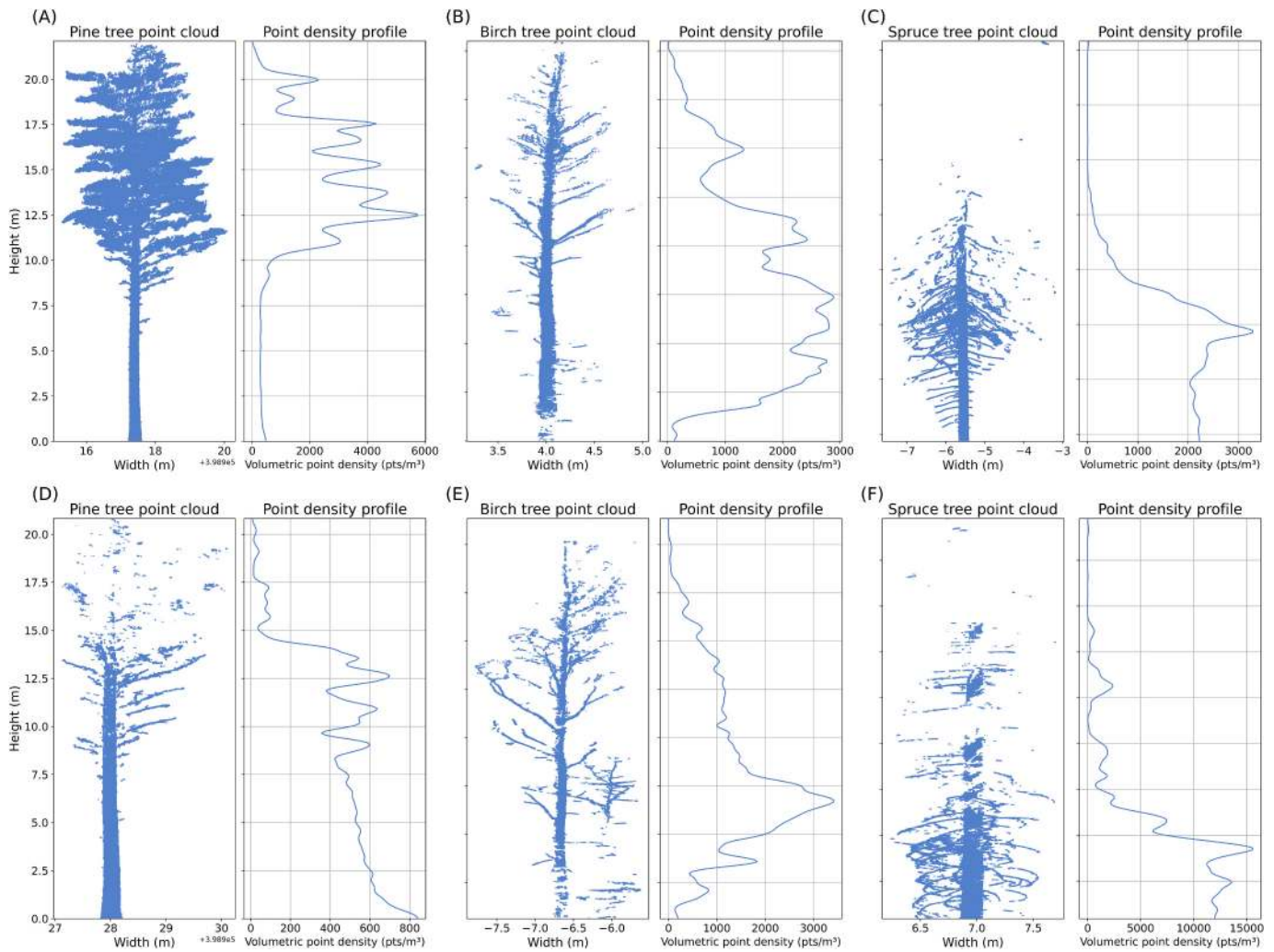


Fig. 9. Point density profiles of tree point clouds with A, B, C – visually intact and D, E, F – visually incomplete QSM reconstructions. The trees have been scanned with TLS.

success. Factors such as occlusion, point density, and the visibility of fine branches may play a more decisive role.

The acquisition geometry of the original point cloud data influences the scope of the study and statistical comparability in temporal analyses. The TLS approach delivers higher data completeness and superior QSM quality when the tree's position optimally aligns with the data collection geometry. It is important to note that the TreeQSM method was originally developed and optimized for extremely dense and compact point clouds merged from multi-scan TLS surrounding a targeted tree. Therefore, higher reconstruction success with plot-level multi-scan TLS data reflects the advantages of TLS-based setups. However, the statistical comparability of QSMs across different time points is reduced by changing scanning geometry across different data collection campaigns, as scanning is conducted from multiple directions during different field operations. Additionally, even the TLS approach shows a decrease in QSM quality at the higher parts of tree canopies. Using TLS has been shown to be challenging for obtaining complete canopy information due to the influence of foliage, branches, and shading (e.g., Liu et al., 2016; Lau et al., 2019). The ultimate choice between the two settings is influenced by specific research objectives, preferences, and constraints. However, given the lack of reproducibility of the unique tower setup, TLS is generally the more reliable and viable approach for obtaining high-quality, reproducible data. Optimal results would come from acquiring data from multiple fixed perspectives. New data acquisition solutions, such as under-canopy drone systems (e.g., Karjalainen et al.,

2024; Liang et al., 2024), may offer greater completeness with minimal additional labor.

5.2. Validation with field measurements

TLS generally outperformed PLS in both DBH and height estimations. DBH errors were consistently lower across all three species in successful TLS QSM models, with birch showing the best performance (MAE = 0.06 cm, RMSE = 0.30 cm), despite having the lowest QSM success rate out of the trees scanned with TLS. This suggests that while the model struggles to generate an intact structure, when it does, the accuracy of the model is high. Pine showed the highest QSM success rate out of the trees scanned with TLS but only moderate validated accuracy, mainly due to missing treetops. Spruce, being the most complex species, had the worst QSM performance, which is expected given its challenging characteristics.

In contrast, PLS QSMs show higher DBH errors, especially for birch (MAE = 1.65 cm, RMSE = 2.33 cm), and were limited by the availability of reference data (only 40 % of the DBH data was available). However, PLS performed better in height estimation for birch (MAE = 0.05, RMSE = 0.12), with minimal error compared to TLS birch models (MAE = 0.53 m, RMSE = 1.09 m). This highlights the potential of PLS for certain data types. PLS QSMs for birch had a higher QSM success rate than those for pine, indicating that birches were generally easier to model and the QSMs captured the entire tree. Pine models struggled the most with

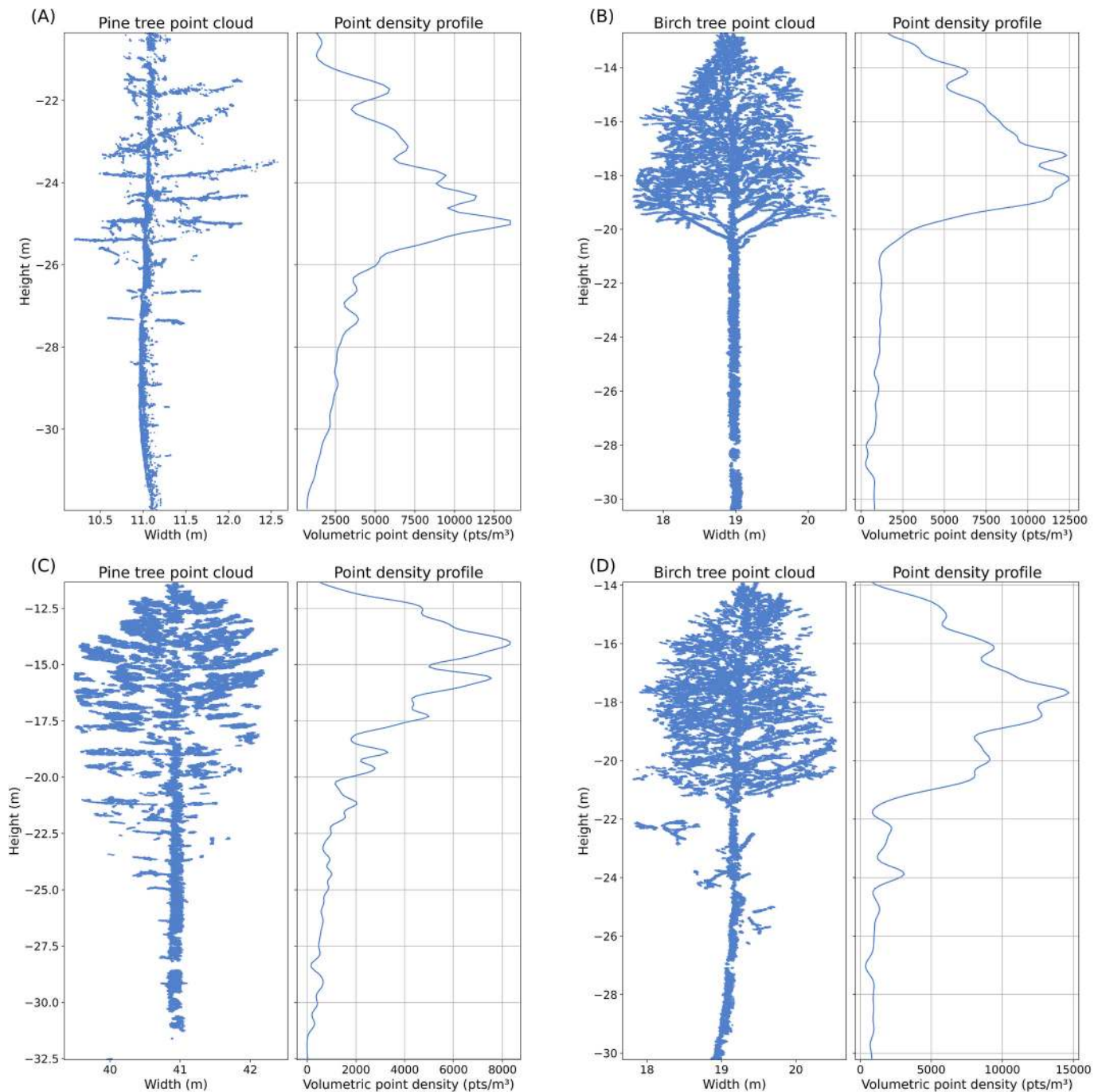


Fig. 10. Point density profiles of tree point clouds with **A, B** – visually intact and **C, D** – visually incomplete QSM reconstructions. The trees have been scanned with PLS. Y-axes reflect local coordinate heights. Negative values reflect the coordinate origin, not below-ground height.

height estimation (MAE = 6.10 m, RMSE = 6.90 m), mainly due to the missing treetops.

Based on the stricter threshold applied by defining a successful QSM as one with an MAE below 1 m and a DBH MAE below 2 cm, the overall success rates remained relatively low, especially for pines scanned with TLS, where only 3.36 % of validated models met both conditions, despite their high initial QSM success. This again highlights how QSM generation does not guarantee accuracy in key metrics, particularly when structural features like the treetop are missing from the model. Birch scanned with TLS had a much higher rate (66.67 %) of realistic DBH and height success. For PLS, birch performed best, achieving the highest rate of successful QSMs with both thresholds, although the validation was limited by the availability of DBH measurements. In contrast, spruce

showed zero success under these criteria despite 100 % of its validated QSMs falling within DBH error limits. Structural complexity seems to complicate accurate model generation even when diameter estimation is acceptable.

5.3. Lessons learnt about tree growth strategy from the bi-temporal QSMs

Statistical distributions of tree-level metrics obtained through QSMs remained consistent across two time points, confirming the fundamental usability of the original point cloud data for temporal analyses. The models preserved overall structural information across timeframes, despite changes in QSM branching orders, structures, and inaccuracies in branch depiction. However, the different temporal scales (one year vs.

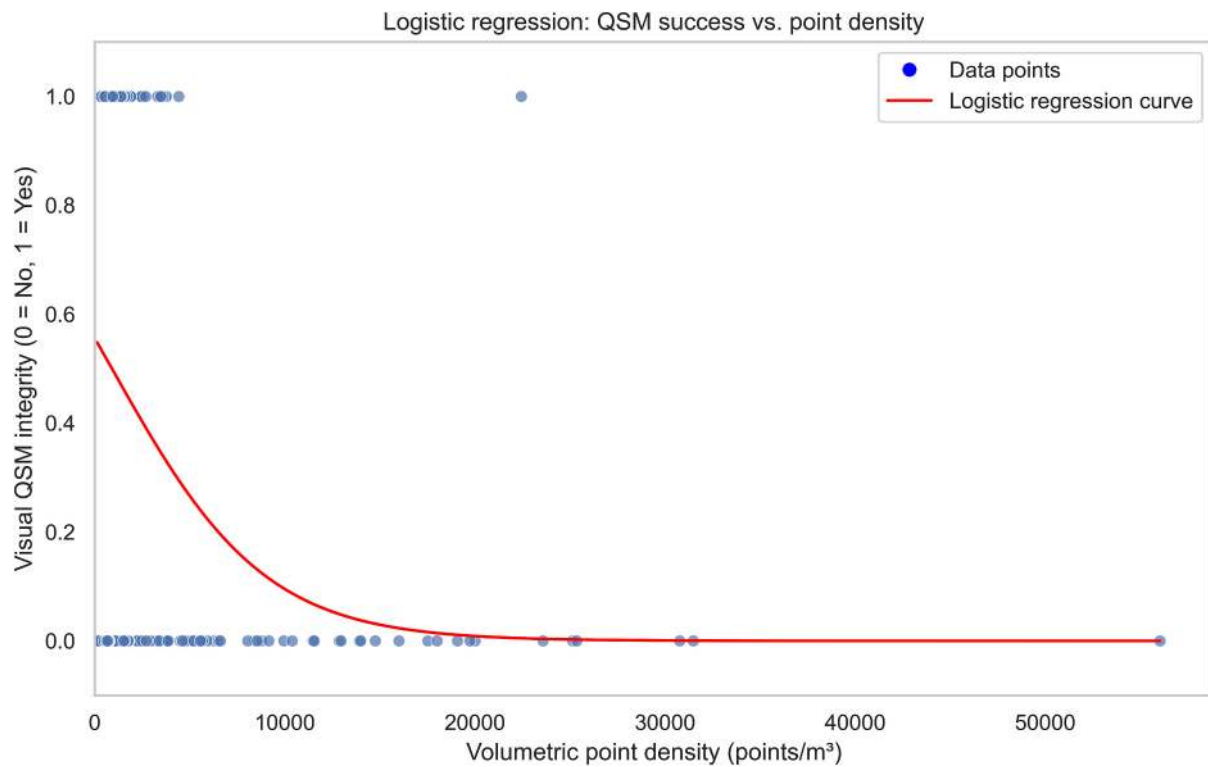


Fig. 11. Relationship between mean volumetric point density and the visual success of QSM generation, visualized using logistic regression. The scatter plot shows individual observations ($n = 232$), where QSM success is coded as a binary variable (1 = visually successful model; 0 = unsuccessful). The red curve represents the fitted logistic regression function. The logistic model reveals a statistically significant negative relationship between point density and QSM success (coefficient = -0.0002 , $p = 0.001$). The model's pseudo R^2 was 0.087, indicating a modest explanatory power. The likelihood ratio test was significant (LLR $p = 1.788 \times 10^{-7}$), confirming the model's improvement over a null model. The model was fit using maximum likelihood estimation (Log-Likelihood = -143.36 , $df = 1$, converged = True). Confidence intervals for the density coefficient did not cross zero (95 % CI: -0.0003 to -0.0001), suggesting a robust effect. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

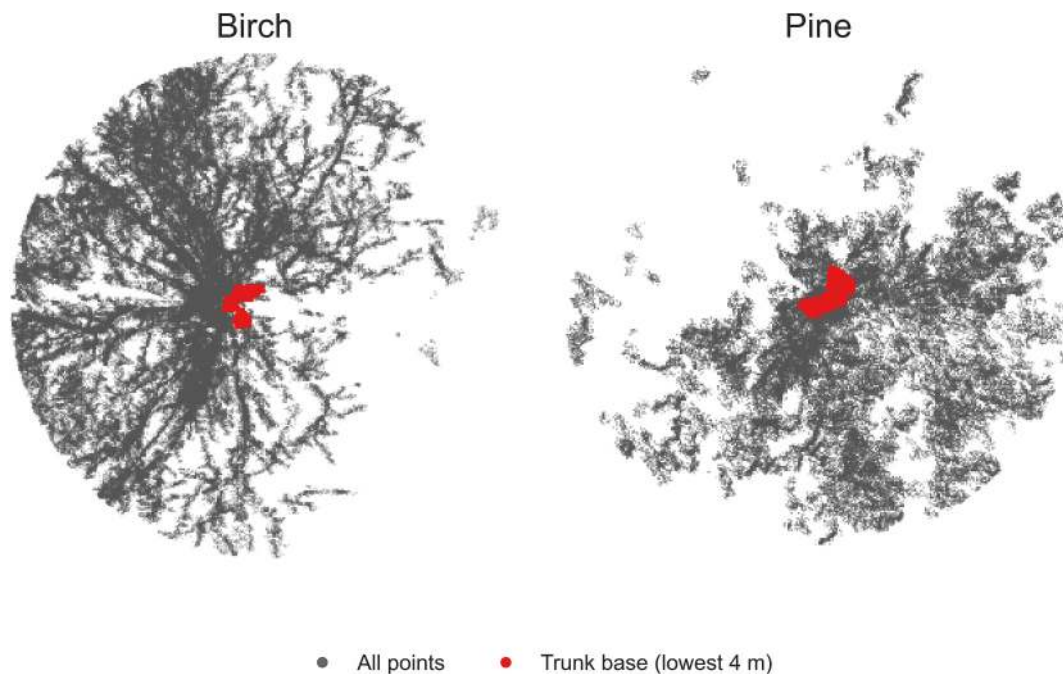


Fig. 12. The effect of the fixed PLS scanning perspective on two tree point clouds. The birch and pine trees are viewed from below, with red points in the middle representing the base of the trunk ($z > 4$ m). Due to the fixed scanning perspective, the trunk shapes appear incomplete, forming semi-circular shapes, and the point clouds show missing sections. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

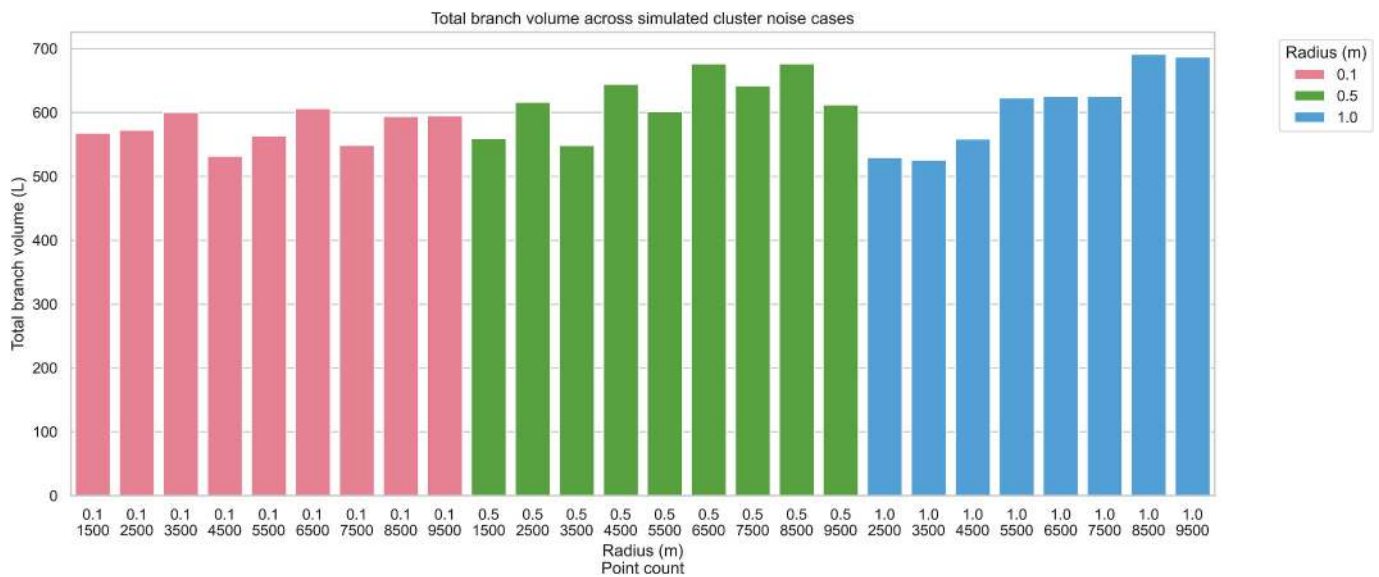


Fig. 13. Total branch volume across the simulated cluster noise cases with varying point counts and radii (0.1, 0.5, and 1.0 m). The same input birch tree point cloud was used. The tree was scanned with PLS. The graph shows the effect of increasing point density within spherical noise clusters on the estimated branch volume, with higher point densities (e.g., 9500 points) generally leading to a higher total branch volume, particularly for larger noise cluster radii (1.0 m).

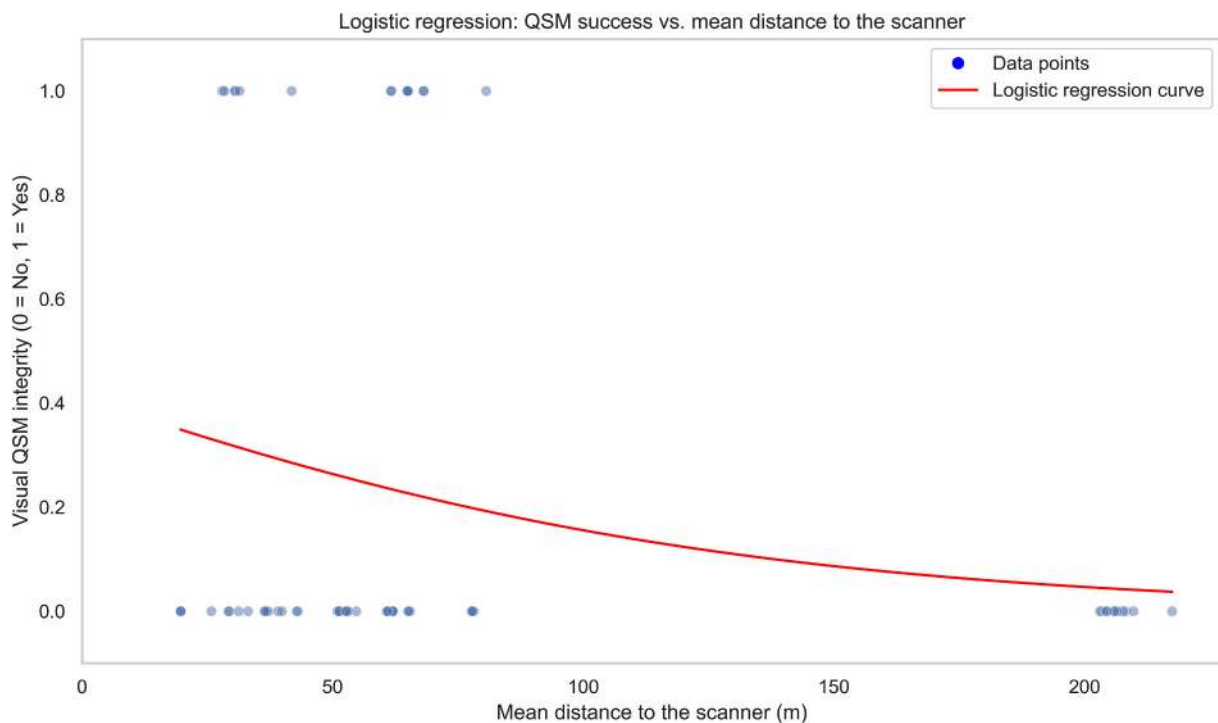


Fig. 14. Logistic regression illustrating the relationship between mean distance to the scanner and the visual success of QSM generation. Each point ($n = 66$) represents a tree with either a successful (1) or unsuccessful (0) QSM based on visual assessment. The red curve represents the predicted probability of QSM success across the range of observed mean scanner distances. The fitted logistic regression model shows a negative trend between the scanner distance and QSM success (coefficient = -0.0133), though the effect was not statistically significant at the 0.05 level ($p = 0.119$). The intercept was also non-significant ($p = 0.516$). The model's pseudo R^2 was 0.055, indicating limited explanatory power, and the overall model fit was marginally significant according to the likelihood ratio test ($LLR p = 0.048$). Maximum likelihood estimation was used (Log-Likelihood = -33.42 , $df = 1$, converged = True), and the 95 % confidence interval for the distance coefficient ranged from -0.030 to 0.003 . (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

five years) limited the comparability of the results and highlight the importance of long-term monitoring to capture clear developmental shifts. Overall, TreeQSM, in its current state, appears well-suited for detecting growth and decline trends over multiple years at the tree level, rather than providing precise values or detecting changes at the individual branch level.

The diverse growth patterns observed among trees of the same species suggest the possibility of distinct growth strategies. Despite sharing genetic similarities, trees of the same species can vary significantly in their growth habits and branching patterns. This variability can be influenced by environmental factors such as temperature (e.g. Chan et al., 2016; Cuny and Rathgeber, 2016; Björklund et al., 2017; Yrttimaa

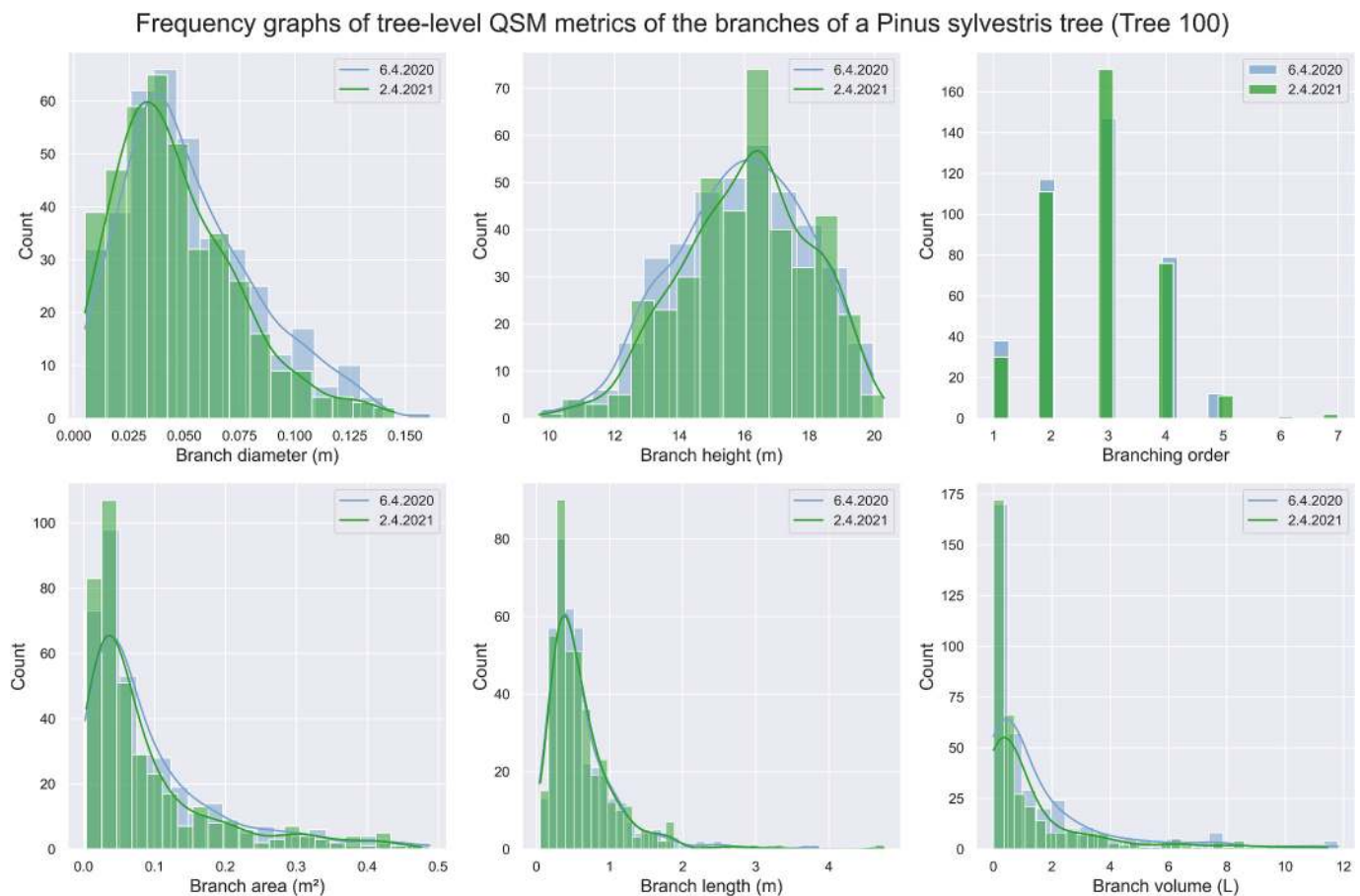


Fig. 15. Frequency graphs of tree-level TreeQSM metrics of the branches of a *Pinus sylvestris* tree with Kernel Density Estimate (KDE) curves. The trunk is excluded due to its large values, which affect readability. The x-axes of the bottom row were limited to the 95th percentile. The point cloud was captured from a single fixed perspective with PLS in Hyytiälä, Finland. The DBH of this tree was 21 cm in 2020 based on a tree-level QSM reconstruction, and its height was 20.4 m. The DBH was 21.68 cm in 2021, and its height was 20.55 m.

et al., 2024), wind (e.g. Dongmo Keumo Jiazet et al., 2022), resource availability such as water balance (e.g. Yrttimaa et al., 2024) and soil water potential (e.g. Chan et al., 2016), tree competence and local species richness (Campos et al., 2024), and genetic predispositions (e.g. Salmela et al., 2024). Trees can also lose branches due to disease, weather damage, or competition for light and resources (e.g., Frelich et al., 2021; Nunes Romeiro et al., 2022). These varying growth patterns may also be influenced by microbiotic and abiotic factors, which warrant further study. Our findings suggest that some trees may allocate resources to produce smaller branches, while others may develop fewer but larger branches. Moreover, our study also confirmed the challenge of species classification when relying on crown architecture (Chen et al., 2024) in point cloud-based approaches and crown texture (Liang et al., 2025) in image-based approaches, due to the variations in branch growth strategies within species. Further investigations are needed to confirm this behavior. It is also important to note that some branches are naturally lost—such as in pines, where the lower branches dry, die, and break over time (e.g. Valentine and Mäkelä, 2005).

5.4. Challenges and advances in pairwise branch identification for bi-temporal QSM comparison

Pairwise branch identification using state-of-the-art QSM generation approaches is challenging due to the rearrangements in QSM branching order, with newly emerged and missing branches. Data acquisition issues, such as gaps in the original point cloud, may also impact the consistency of branching order. Accurately identifying branches between different time points becomes difficult due to evolving branching

patterns, and significant changes can greatly affect the logical consistency of bi-temporal branch comparisons. However, tracing the geometric metrics (e.g., branch angle, diameter, and length) of a specific branch over time can significantly improve our understanding of the ecophysiological processes of trees. Prioritizing the analysis of the largest lower branches or trees with relatively fewer small branches may lead to more reliable temporal comparisons. Côté et al. (2011) also found that modeling the architecture of the main branches could offer a solution. New approaches, such as Qi and Liang (2024), which identify and analyze the positions of branch cylinders, may address these challenges by incorporating height information and considering branch orientation angles.

5.5. Constraints of the findings

The constraints of this study are summarized to highlight potential risks to the generalizability and reproducibility of its findings.

First, tree architecture strongly affects QSM performance. Pine, with its relatively simple crown structure, achieved a much higher TLS success rate, whereas birch and spruce, with finer and more complex branching patterns, proved far more challenging. This demonstrates that QSM outcomes remain structure-dependent and not universally applicable. Moreover, crown architecture is shaped by local environmental conditions, such as snow load, wind exposure, or past disturbance. These factors, though not explicitly controlled for, can strongly affect reconstruction reliability. Therefore, our findings are limited to the three studied boreal tree species.

Second, the success of QSM generation is also dependent on input

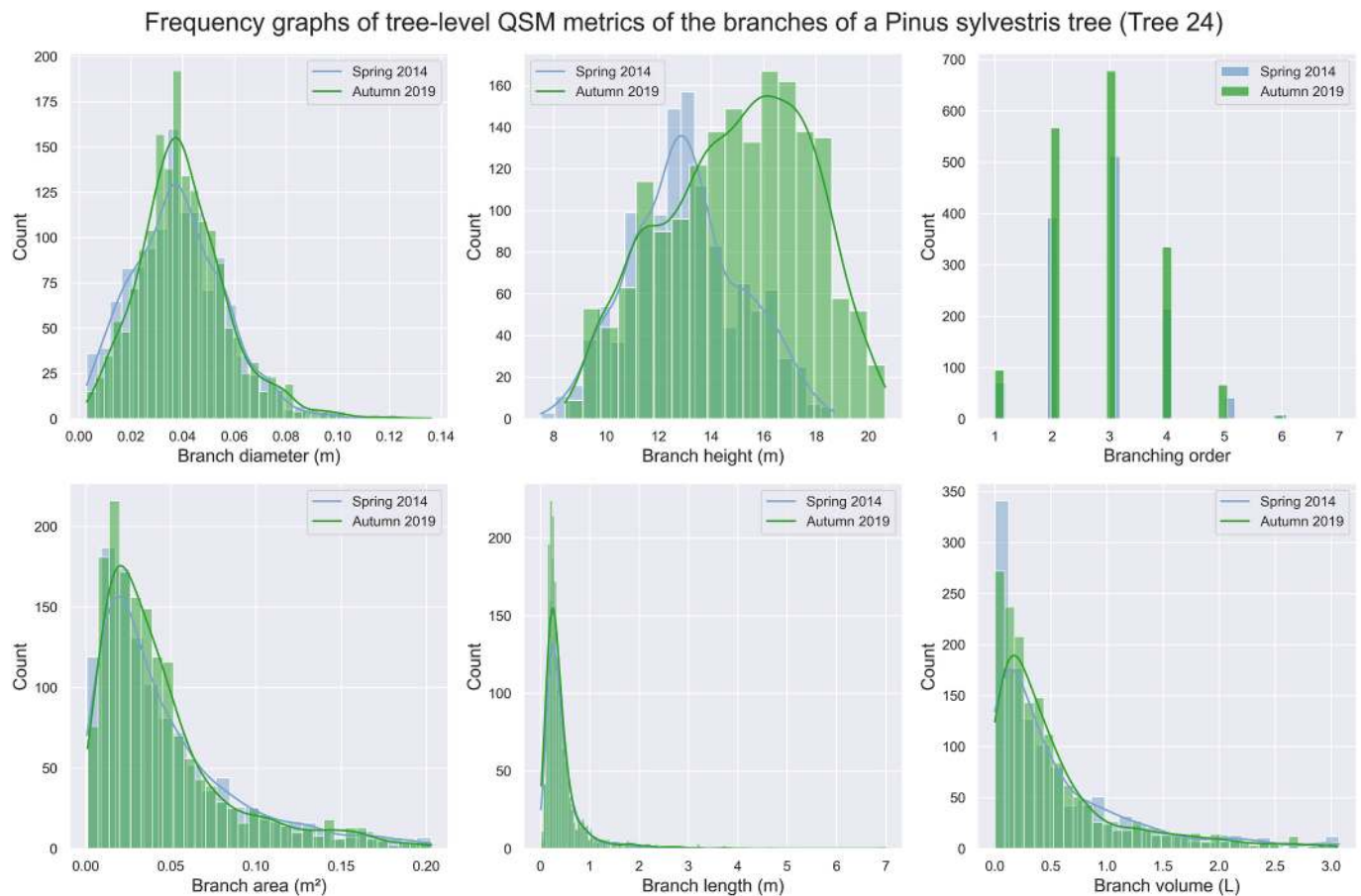


Fig. 16. Frequency graphs of tree-level TreeQSM metrics of the branches of a *Pinus sylvestris* tree with Kernel Density Estimate (KDE) curves. The trunk is excluded due to its large values, which affect readability. The x-axes of the bottom row were limited to the 95th percentile. The point cloud was captured from multiple perspectives in Evo, Finland. The DBH of this tree was 22.68 cm in 2014 based on a tree-level QSM reconstruction, and its height was 18.85 m. The DBH was 23.98 cm in 2019, and its height was 20.99 m.

data characteristics. TreeQSM was originally developed and optimized for dense, static TLS point clouds, which partly explains the higher TLS success compared to sparser and noisier point clouds from other sources, such as PLS. This coupling limits the transferability of the TreeQSM + TLS method to alternative point cloud sources and emphasizes that reported results are conditioned by the sensor-algorithm interaction. Our results demonstrate the limited adaptability of the TreeQSM generation approach across sparser and noisier data scenarios.

Finally, the reported success rates are based on relatively small absolute numbers of individual trees per species. For example, only three successful TLS birch reconstructions were obtained. However, such an outcome reveals the reality for QSM generation when the data collection did not follow an ideal setup. The study provides a transparent assessment of where QSM approaches succeed and where they struggle, and, as an outcome, offers recommendations on the minimum data requirements needed for reliable QSM generation. In this sense, the work serves as guidance for future methodological development and a reference for data preparation when using state-of-the-art QSM generation approaches.

6. Conclusions

Our study investigated the potential and challenges of temporal branch-level studies, refining QSM methods to support forestry research. Our results highlight the current performance of QSM across species and sensors, revealing where the method succeeds and where it struggles under specific boundary conditions. This study provides insights for the development of advanced remote sensing technologies aimed at

enhancing sustainable forest management and ecosystem monitoring. We address the challenge of identifying branch correspondences across different time points and emphasize the importance of selecting specific point clouds and branch types known for their consistent modeling characteristics. While dedicated QSM methods for temporal studies have yet to be established, potential solutions exist. One approach involves developing a method to identify branch correspondences across different time frames using multiple QSM metrics and additional information, such as branch location. Despite limitations, QSMs can statistically compare growth trends, and with further improvements, they may offer more precise change detection.

Temporal QSM studies emphasize data quality, particularly point cloud acquisition geometry, point density, and data completeness, which are crucial for accurate growth detection. Our findings highlight the role of QSM technology in revealing intra-species tree growth strategies. Future research could explore the underlying mechanisms that shape the variations in QSM growth patterns, including both physiological processes and environmental influences. Such investigations could uncover the complexities of forest ecosystem dynamics and inform forest management strategies aimed at promoting biodiversity and ecosystem resilience. The results point to the need for refinement and innovation in QSM technology to enhance forest monitoring and management practices. While improvements are needed to isolate foliage-related effects from actual tree structure changes, QSM remains a promising tool for tracking growth trends over extended periods, providing valuable insights for sustainable forest management.

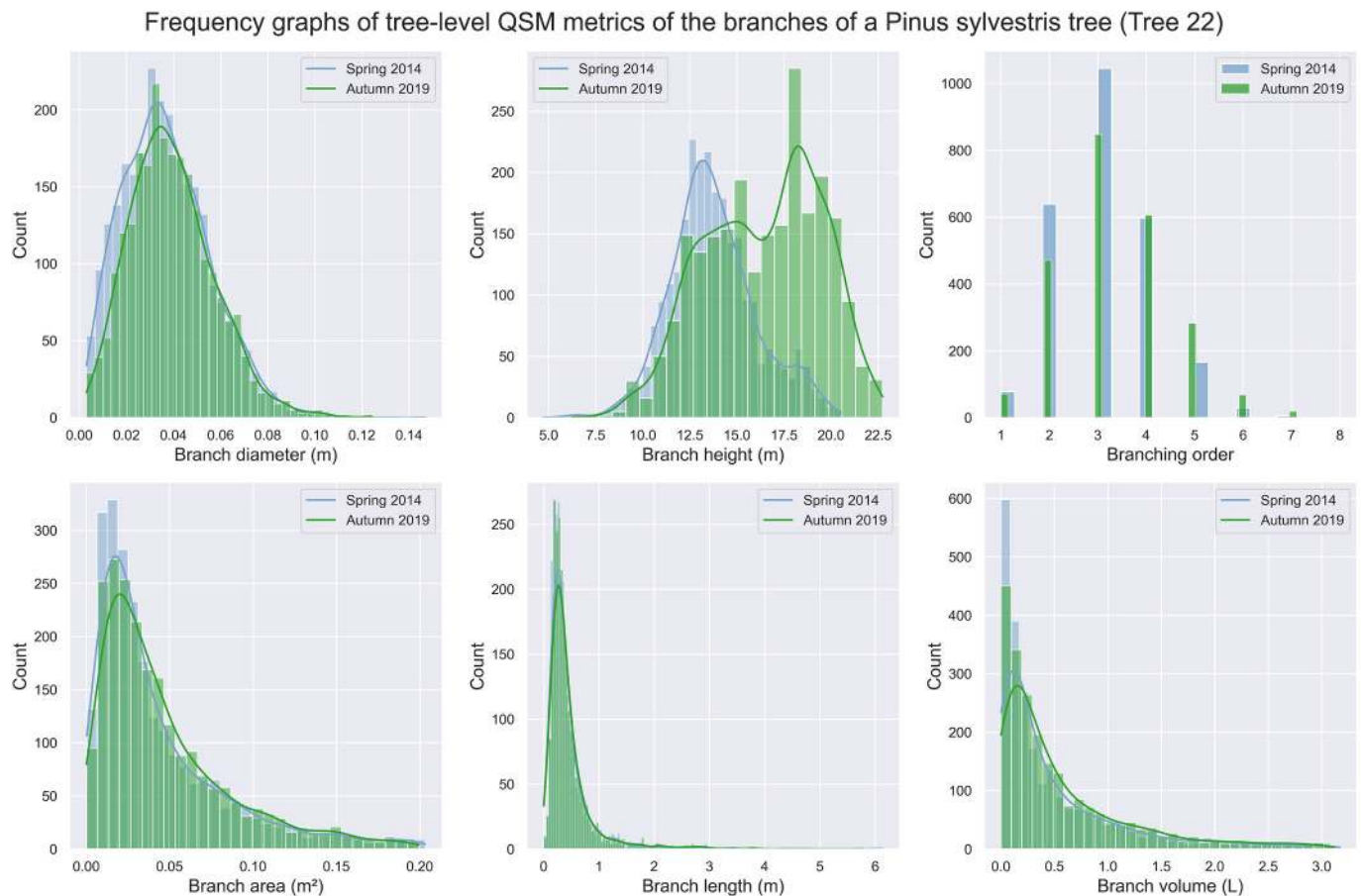


Fig. 17. Frequency graphs of tree-level TreeQSM metrics of the branches of a *Pinus sylvestris* tree with Kernel Density Estimate (KDE) curves. The trunk is excluded due to its large values, which affect the readability. The x-axes of the bottom row were limited to the 95th percentile. The point cloud was captured from multiple perspectives in Evo, Finland. The DBH of this tree was 26.6 cm in 2014 based on a tree-level QSM reconstruction, and its height was 20.69 m. The DBH was 28.44 cm in 2019, and its height was 22.89 m.

Research data for this article

The data used in this study is publicly available and can be accessed through the following repositories: The Terrestrial Laser Scanning (TLS) data from Evo can be found at the Finnish Research Infrastructure website <https://research.fi/en/results/dataset/e82817e2-07c9-4f28-8c6e-402e7196fb75> (data collected in 2019) and <https://research.fi/en/results/dataset/b3498c83-561e-4ebd-a889-21365e9f90bc> (data collected in 2014). The Permanent Laser Scanning (PLS) data from Hyytiälä is available at Etsin - Finnish Data Archive <https://etsin.fairdat.fi/dataset/55b8734a-6827-4ae1-ae97-89378977853b>.

CRedit authorship contribution statement

Hanna Elisabet Sorokina: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis. **Mariana Campos:** Writing – review & editing, Validation, Investigation, Data curation. **Pasi Raunonen:** Writing – review & editing, Validation, Methodology, Investigation. **Anna Shcherbacheva:** Writing – review & editing, Validation, Methodology, Investigation. **Rami Echriti:** Writing – review & editing, Validation, Data curation. **Juha Hyypä:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition. **Eetu Puttonen:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition. **Yunsheng Wang:** Writing – review & editing, Validation, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT-4 to enhance readability and suggest better ways to express certain ideas. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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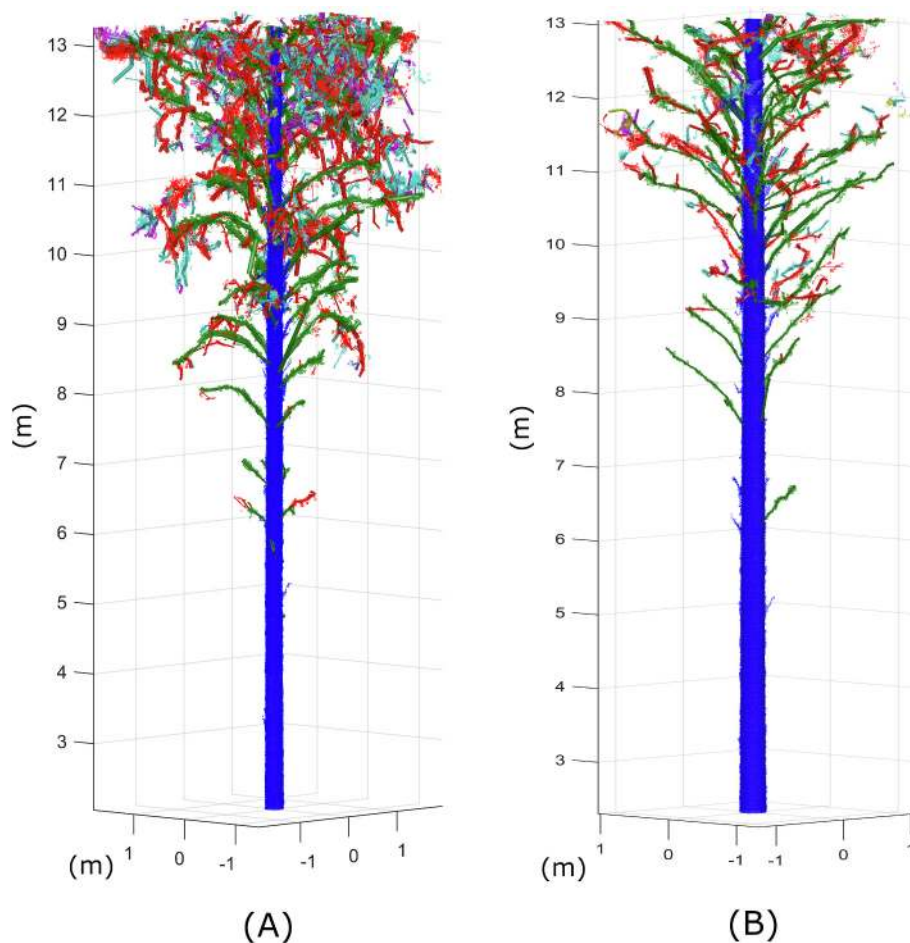


Fig. 18. Zoomed-in visualizations of QSMs depicting the largest branches from the middle section of a pine tree (TLS approach, tree 22). Blue represents the trunk (branching order 0), green indicates the branching order 1, red indicates the branching order 2, turquoise indicates the branching order 3, purple indicates the branching order 4, and yellow indicates the branching order 5. A – Data from 2014 and B – data from 2019. Main branches (branching order 1) appear to have been modeled with less variability across the two time points compared to the smaller branches. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

services and nature conservation via the integrative approach” [grant number 101135263].

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.

Data availability

I have shared the links to my data.

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