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Assessing forest structural complexity: insights from alternative laser scanning approaches

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ABSTRACT
This study evaluates the potential of low-altitude airborne laser scanning (ALS) and terrestrial laser scanning (TLS) for characterizing structural complexity in Southern Finland. Unlike species diversity, structural complexity reflects realized niche occupancy by describing how vegetation utilizes light, water, and space, providing key insights into ecosystem functioning. We analyzed 99 circular sample plots (*r* = 20 m) scanned with helicopter-borne ALS at 80 m altitude and TLS data from nine scan locations per plot. Structural complexity metrics were derived at both grid level (variability in canopy height models and voxel occupancy) and object level (variability in individual tree attributes). High-density ALS effectively captured vertical and horizontal complexity through object-level analysis, showing close agreement with TLS. However, differences in measurement geometry affected volumetric complexity, with ALS and TLS characterizing tree architecture and vegetation occupancy differently. Object-level approaches captured a broader range of horizontal and vertical complexity, while grid-level approaches better captured volumetric variability, facilitating the identification of forest stand properties and biodiversity hotspots. The strongest agreement between ALS and TLS occurred for variation in tree height ($R^2 = 0.66$, Spearman = 0.80), while lowest agreement was found for fractal dimensions of tree architecture ($R^2 = 0.04$, Spearman = 0.25).

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KEYWORDS
Structural complexity; ALS; TLS; Boreal forests

Introduction

Global ecosystems face increasing anthropogenic pressures, demanding advanced tools to mitigate impacts and manage resources sustainably (European Commission 2021). Structural complexity, defined as the variation in size, shape, and spatial arrangement of vegetation, has proven to be a strong predictor of ecosystem productivity, biodiversity, and habitat availability (Carrasco et al. 2019; LaRue et al. 2023). High structural complexity enhances biomass productivity by promoting resource efficiency and complementary interactions among vegetation layers. However, it may reduce merchantable wood yield, as competition and irregular growth patterns can limit the quantity and quality of timber (Hynynen et al. 2005; Zenner 2016). Despite this trade-off, structural complexity significantly improves forest resilience by fostering functional redundancy and stability, enabling forests to better withstand disturbances like pests, diseases, and extreme weather (Fahey et al. 2015; Huuskonen et al. 2021). Compared to species diversity, which measures the potential niche spaces, structural complexity reflects realized niche occupancy – capturing how vegetation uses light, water, and space more directly providing more reliable insights into forest health and adaptive capacity. This makes it an essential tool for sustainable forest management and conservation planning. Forest structural complexity can be assessed using conventional field measurements (McElhinny et al. 2005), however, Light Detection and Ranging (LiDAR) based methods such as laser scanning offer significant advantages, including greater time and cost efficiency, the ability to capture fine-scale structural details, and the capability to quantify lower vegetation layers that are challenging to measure using traditional approaches (Campbell et al. 2018). LiDAR based structural complexity assessment offers a pathway also for large-scale biodiversity mapping as the structural complexity has a significant impact on biodiversity characteristics, and thus structural complexity metrics can be used as proxies for broader ecological processes (Franklin Jerry and Van Pelt 2004).

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However, quantification of the forest structural complexity requires accurate assessment of vertical, horizontal, and three-dimensional (volumetric) characteristics of the forest stands. These dimensions characterize the abundance of vegetative structures, representing the domain for photosynthesis, and are therefore closely linked to the ecological functions and yield of a forest stand (Seidel and Ammer 2023). In contrast to conventional forest inventories, laser scanning has the capability to quantify the structural complexity (vertical, horizontal and volumetric) of different vegetation layers (i.e. low vegetation, individual trees and tree communities) in forest environment (Shugart et al. 2010; Sverdrup-Thygeson et al. 2016). Previous studies have demonstrated the capabilities of airborne and terrestrial laser scanning (ALS and TLS) point cloud data to identify individual trees, and to analyse the height variability of the trees and tree communities (Peuhkurinen et al. 2011; Liu et al. 2018), and proved the potential to characterize vertical complexity of a forest stand based on canopy height model (CHM)(Vastaranta et al. 2013; Torresan et al. 2014; Okojie et al. 2020). Horizontal complexity can be assessed through investigating the variation in crown area of individual trees and canopy cover at forest stand-level (Maltamo et al. 2014). These metrics reflect variability in crown sizes and canopy cover, providing insights into horizontal structural diversity (Vehmas et al. 2011; Yrttimaa et al. 2020). Volumetric complexity at the object-level can be assessed by examining the variability in the architectural complexity of individual trees using, e.g. fractal dimensions (box dimensions; Seidel 2018), while vegetation occupancy within predefined voxel cells could be used to assess volumetric complexity at the grid level (Ross et al. 2022). These metrics aim to capture variations in both vertical and horizontal tree dimensions and consider the spatial arrangement of vegetative structures, providing insights into three-dimensional structural complexity (Neudam et al. 2023).

Advances in ALS and TLS technologies enable higher point densities and faster data acquisitions for structural complexity assessment, but both methods face limitations due to occlusion causing decline of point cloud quality. The challenge for ALS is to comprehensively quantify the characteristics of lower canopy layers and low vegetation structures (Hamraz et al. 2017; Venier et al. 2019). In contrast, TLS has limitations in capturing the characteristics of the top canopy (Srinivasan et al. 2015; Yrttimaa et al. 2020). These limitations arise primarily because of the field of view difference between the systems: ALS data is collected above the canopy while TLS data acquisition is conducted below the canopy. It has therefore remained unclear whether low-altitude ALS (i.e. > 500 points / m^2) collected from helicopter or a drone platform (see, e.g. Persson et al. 2022) and TLS datasets provide consistent results across vertical, horizontal, and volumetric complexity dimensions or whether differences in scanning geometry and analytical methods influence the outcomes. This gap is critical to address for identifying efficient and scalable methods for structural diversity mapping and its application in predicting forest productivity and biodiversity. Recently, (Kacic et al. 2025) reported correlations of 0.5–0.8 between TLS and mobile laser scanning as well as lower resolution space-born observations among different metrics of structural complexity within Central-European mixed-species forests, providing insights for intra-platform consistency.

To address the realized knowledge gap, this study utilizes helicopter-borne (heli-ALS) and TLS point cloud data to compare object-level and grid-level approaches for assessing forest structural complexity across vertical, horizontal, and volumetric dimensions of southern boreal forest stands. For each sample plot, vertical complexity is evaluated as tree height variability (object-level metric) and CHM variation within the plot (grid-level metric). For horizontal complexity assessment, crown area variability and canopy cover variation are used as the object-level and grid-level metrics, respectively. Then, volumetric complexity is examined at the object-level as architectural variability of individual trees' fractal dimensions (box-dimensions) and at the grid-level as voxel-based vegetation occupancy. These metrics allow us to evaluate whether the object-level approach captures a broader range of structural complexity than the grid-level approach and whether the utilized laser scanning method influences the observed complexity patterns. Using the coefficient of variation (CV) as a standardized measure of metric variability within each plot, we assess the capability of both sensors and approaches to capture structural diversity. These findings are expected to have important implications for forest management, providing tools to predict ecosystem productivity and biodiversity. We aim to answer the following research question (RQ) and to verify the corresponding hypotheses (H).

RQ: Can the structural complexity (in a vertical, horizontal, or volumetric dimensions) of a forest stand be quantified consistently between heli-ALS and TLS point cloud data using either object-level or grid-level analysis?

H1: Heli-ALS can capture a larger range in structural complexity related to vertical variation compared to TLS due to better tree height estimation capacity.

H2: TLS can capture a larger range in structural complexity related to horizontal and volumetric analysis than heli-ALS due to better capacity to characterize vegetation below canopy.

H3: Object-level approach will capture a statistically significantly larger range of metric variability compared to grid-level metrics due to its tree specific analysis.

H4: Due to the great details captured by both techniques, there is a strong agreement between the structural complexity metrices when derived using different observation techniques or analysis methods.

Materials and methods

Experimental design

The experiment was conducted within the research site in Evo, Finland (61°11′48.87′′ 25°6′27.9′′) which belongs to the southern boreal forests dominated by Scots pine (*Pinus sylvestris* L.) and Norway spruce (*Picea abies* (L.) H. Karst). In total, we used ninety-nine fixed-sized circular sample plots with a radius of 20 m (Figure 1A and B). The sample plots were initially established to cover the variation in different forest structures within the research site (see Yu et al. 2015). A grid (32 m × 32 m) was overlaid on the area, and sparser ALS point cloud-based metrics describing forest vegetation height and density at 2 m height were calculated for each grid cell. Sample plots were then selected to represent the most diverse canopy heights and canopy covers, while ensuring that plots were not placed in stands at different developmental stages. The geographic coordinates of the plot centers were determined using a total station (Trimble 5602), which was oriented to the local coordinate system using ground control points measured with VRS-GNSS (Trimble R8) on open areas close to the plot. The sample plots include both managed, young, and mature as well as conserved, old-growth forests featuring both single- and mixed-species as well as single-layered and multi-layered forests (Figure 1C).

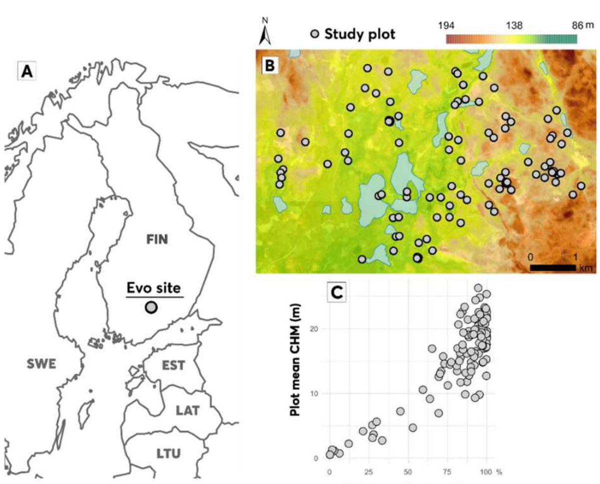

Figure 1. (A) The location of the research site Evo in southern Finland (FIN). (B) Placement of sample plots within the research site illustrated on a digital elevation model. (C) Scatter plots show structural variability of the sample plots with respect to plot mean CHM height value and CHM based plot mean canopy cover %.

Laser scanning point cloud data acquisition

The TLS campaign took place in April-May 2021. Each sample plot was scanned from multiple locations: one scan from the plot center and eight auxiliary scans from positions distributed around the plot. We used a Leica RTC360 3D time-of-flight scanner which operates at a 1550 nm wavelength, featuring a 0.5 mrad beam divergence and a 6 nm (1/e2) beam diameter at exit. Each scan produced a point cloud with 300° vertical and 360° horizontal field-of-view and an angular resolution of 0.034°, resulting in a point spacing of 3 mm at a 10-m distance. All the scans from each of the sample plots were co-registered and merged in a Leica Cyclone Register360 software using reference targets (spheres with radius 198 mm) attached to trees, approximately five to six per sample plot. The indicative point cloud density was, on average, 28 000 pts/m^2.

The helicopter-borne ALS dataset (i.e. heli-ALS) was collected from a helicopter on June 22nd, 2021. Each sample plot was scanned from altitude of 80 m above ground level and 50 km/h flight speed (Figure 1). The scanning system consisted of three Riegl scanners: VUX-1HA, MiniVUX-3UAV, and VQ-840-G. Point cloud trajectory was calculated with Wypoint Inertial Explorer (NovAtel Inc., Canada) software and location postprocessed with base station for differential correction at the location (61°0′2.021′′ 24°59′54.16′′). Point cloud was registered in RiProcess (Riegl Laser Measurement Systems GmbH, Austria) reaching an overall point cloud density of 1 800 pts/m^2, which is notably higher than a conventional ALS point cloud data (i.e. 0.5–30 pts/m^2; Fuhr et al. 2022; Kaartinen et al. 2012).

Point cloud data pre-processing

The initial preprocessing of the acquired point cloud data (both heli-ALS and TLS) included following steps: First, we applied a 5-m buffer around the sample plots to ensure that all relevant trees, also those located close to the sample plot borders, became fully characterized. Heli-ALS and TLS point clouds were clipped according to the buffered (20 m + 5 m) boundaries to delineate the areas of interest for further processing. To remove the topography from the point clouds, we performed a standard height-normalization procedure using the lasground tool in LAStools software (rapidlasso GmbH, Gilching, Germany). Then we created CHMs from both heli-ALS and TLS with a resolution of 0.5 m. The 0.5 m resolution was chosen because it has been commonly used in studies within the same research site (Kankare et al. 2014; Vastaranta et al. 2011), offering a balance between a too fine resolution introducing noise to hinder tree detection, and a too coarse resolution to lead to tree merging and lower detection rates. Individual tree detection (ITD) was performed separately for TLS and heli-ALS based on the created CHMs and a marker-controlled watershed segmentation algorithm employing local maximum filtering with variable window size (w) (Popescu and Wynne 2004) (Equation 1).

$$w = (1 + 0.07 * h)/2/0.5 \qquad (1)$$

where h represents the height above the ground within CHM pixels. To assign point cloud classification according to the identified crown segments, we conducted individual tree segmentation (ITS) applying the Dalponte2016 algorithm (Dalponte and Coomes 2016) utilizing CHM and the identified tree locations as inputs.

Trees with the identified tree top locating inside the 20-m radius sample plots and crown boundaries inside the extended plots ($r = 25$ m) were considered for further analysis. For the object-based approach, the presence of the crowns of these detected trees defined the actual boundaries of the sample plots (Pascual 2019). To evaluate grid-level structural complexity metrics, each study plot was divided into six equal-sized sectors (Figure 2B), allowing to quantify intra-plot variability for vertical, horizontal, and volumetric complexity metrics and calculate comparable CV for each plot.

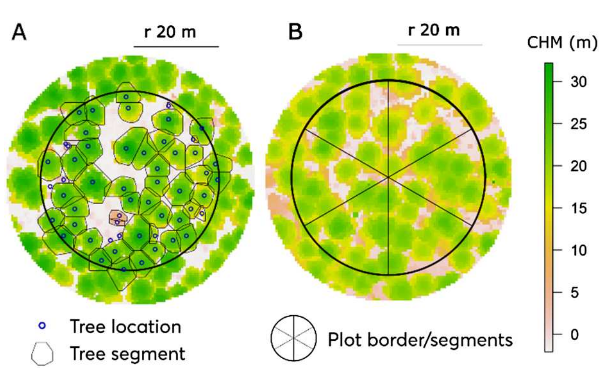

Figure 2. Top-view illustration of canopy height models (CHM) and description of the geometry of the sample plots in object- and grid-level approaches. (A) An oversized sample plot was used for tree detection and crown segmentation to mitigate the edge-effect in the object-level approach. (B) The study plots for grid-level metrics were divided into six equal-sized sectors to assess intra-plot variability in the investigated metrics.

Methods to assess structural complexity using TLS and ALS point clouds

To compare the capability of heli-ALS and TLS point cloud data in forest structural complexity characterization we calculated metrics characterizing horizontal, vertical, and volumetric complexity using both grid-level and object-level approaches. We aimed to use such metrics that would provide a somewhat simplified characterization of the stand structure to account for the obvious differences between the data acquisition methods. The grid-level approach meant analyzing variation in filled voxel distribution and assessing CHM characteristics while the object-level approach meant analyzing variation in individual tree properties. We calculated a plot level estimate for the CV for all the structural complexity metrics. The outline of this methodology is visualized in Figure 3 and described in more detail in the following subsections.

Horizontal complexity assessment

Object-level horizontal structural complexity was estimated as the CV in the obtained ITS-derived individual tree crown area, considered as the horizontal tree characteristic, within the plot (Figure 3, A1).

Grid-level horizontal structural complexity was estimated using CV in mean canopy cover among the six sectors for each study plot (Figure 3, B1). Canopy cover was estimated as the ratio of the number of CHM pixels above 3 m (considered to represent canopy coverage) to the total number of CHM pixels within the sector (including canopy gaps).

Vertical complexity assessment

Object-level vertical structural complexity was estimated by calculating the CV in the height of the identified trees in each study plot. Tree height estimations, considered as vertical tree characteristics, were based on ITS calculating height difference between the highest and lowest point in each tree segment (Figure 3, A2).

Grid-level estimation of vertical structural complexity was computed as CV of mean CHM values in each of six sectors established for each study plot (Figure 3, B2).

Volumetric complexity estimation

Object level volumetric complexity was estimated using individually segmented tree point clouds and their box dimension values (Figure 3, A3). Box dimension is a measure of how complex the structure of an object is, based on the number and size of voxels that are

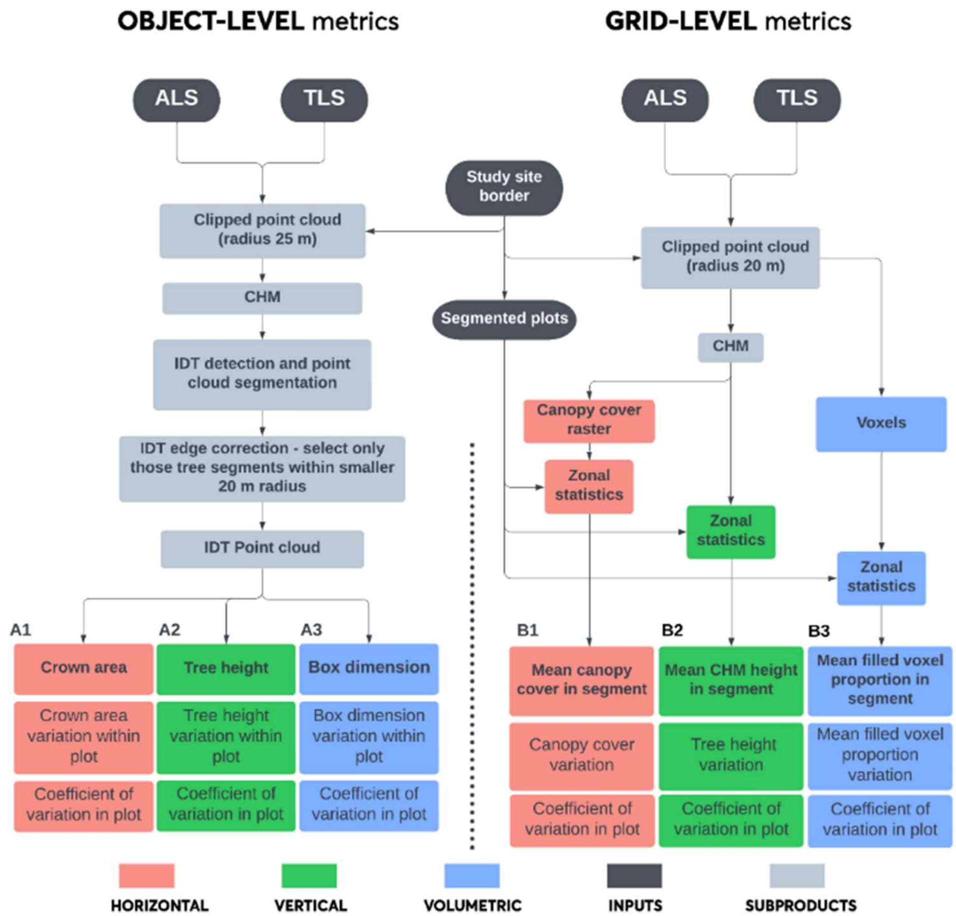

Figure 3. Helicopter-borne laser scanning (ALS) and terrestrial laser scanning (TLS) point cloud processing workflow for computing each structural complexity metric characterizing the structural variation in (1) horizontal, (2) vertical, and (3) volumetric space, obtained using (A) the object-level approach (i.e. assessment of the variability of individual tree characteristics) and (B) the grid-level approach (i.e. assessment of the variability of canopy height model (CHM) characteristics). This led to six alternative ways for describing the structural complexity that were object-level horizontal (A1), object-level vertical (A2), object-level volumetric (A3), grid-level horizontal B1, grid-level vertical (B2) and grid-level volumetric (B3).

needed to contain the point cloud. Box dimension was estimated using R software (version 4.1.1) package VoxR (Lecigne et al. 2018) as the slope of a straight line fitted to a plot where the y-axis shows the natural logarithm of the number of voxels (N) and the x-axis shows the natural logarithm of the inverse voxel size (1/r). A higher box dimension means the structure is more complex. Finally, we computed CV of box-dimensions for each study plot.

Grid-level volumetric complexity was estimated as filled voxel proportion. To address differences between the scanning geometries of TLS and heli-ALS, we analyzed filled voxel proportions for a subset of point clouds where both technologies were assumed to convey rather similar reconstructions. This subsetting included removing points below one meter and above top 80% of the stand maximum height as observed from the heli-ALS data better representing the top of the trees. Points below one meter represent returns from the terrain and ground vegetation which could be oversampled with TLS compared to heli-ALS. In the same way, points above 80% of the stand maximum height represent the top of tree canopies which were assumed to be oversampled with ALS compared to TLS (Neudam et al. 2023). Thus, focusing on the height range above 1 meter and below 80% of stand height was assumed fair considering differences in the measurement geometries between TLS and heli-ALS (Figure 3, B3). The subsampled point cloud was further converted into 20 cm voxels as the same voxel size has also been previously used (Juchheim et al. 2017). We removed empty voxels and remained occupied voxels - containing at least one laser return per voxel. Then we calculated vegetation occupancy as the ratio of the volume of voxels occupied by vegetation to the volume of a cylinder with radius corresponding to the sample plot radius and height corresponding to the investigated height interval from 1 m to 80% plot height. Finally, we computed CV in the vegetation occupancy within the six sectors in each sample plot.

Statistical analysis to evaluate differences in structural complexity estimates between obtained techniques and analysis methods

To evaluate the validity of H1 and H2, we applied F-statistics to test whether the variances in the TLS-based complexity metrices and their heli-ALS-based counterparts deviated from each other with 95% confidence (p-value < 0.05). Similarly, we assessed whether the variances in the object-level metrics and their grid-level counterparts deviated from each other (H3).

To validate H4, we quantified the level of agreement between structural complexity metrics when derived using heli-ALS and TLS. To do so, we used coefficient of determination (R^2) to assess the strength of a linear relationship between the obtained complexity metrics. In addition, we evaluated the degree of similarity in forest stand complexity rankings based on the obtained structural complexity measures between the metrics and data sources used. The sample plots were arranged in a descending order based on each metric at a time (vertical, horizontal, volumetric), and these rankings were compared between heli-ALS and TLS as well as between object-level and grid-level with Spearman's rank correlation coefficient utilized as a non-parametric measure of statistical dependence.

Results

Structural complexity metric range comparison

Our investigations revealed that TLS and heli-ALS captured rather similar ranges of structural complexity variability across the investigated sample plots when the same analysis method (object-level or grid-level approach) was used for deriving the metrics (Figure 4). The only statistically significant ($p > 0.05$) intra-platform difference was noticed when the object-based approach was used for volumetric complexity assessment, where TLS captured a larger range (0.142 vs. 0.105) compared to heli-ALS.

For heli-ALS horizontal metrics, crown area CV (object-level: min 0.356, max 0.883, range 0.526) exhibits greater variability than canopy cover CV (grid-level: min 0.00355, max 0.402, range 0.399). TLS shows a similar pattern, with crown area CV (object-level: min 0.403, max 0.928, range 0.525) exceeding canopy cover CV (grid-level: min 0, max 0.367, range 0.367).

Vertical metrics follow the same trend. Heli-ALS crown height CV (object-level: min 0.0946, max 0.701, range 0.606) is more variable than CV of CHM (grid-level: min 0.0280, max 0.410, range 0.382). TLS crown height CV (object-level: min 0.103, max 0.611, range 0.508) also surpasses CHM CV (grid-level: min 0.0240, max 0.452, range 0.428).

Volumetric metrics deviated slightly. For heli-ALS, box-dimension CV (object-level: min 0.09, max 0.195, median 0.105, range 0.105) shows less variability than filled voxel proportion CV (grid-level: min 0.370, max 0.958, median 0.588, range 0.588). TLS results align, box-dimension CV (object-level: min 0.135, max 0.277, median 0.142, range 0.142) being less variable than filled voxel proportion CV (grid-level: min 0.201, max 0.696, median 0.495, range 0.495).

The object-based approach seemed to capture statistically significantly larger ($p > 0.05$) range in horizontal and vertical dimensions while the grid-level approach yielded statistically significantly larger range in volumetric complexity regardless of the observation technology used (Figure 4).

Structural complexity metric correlation and agreement comparison

The highest association between heli-ALS and TLS for structural complexity assessment was recorded between object-level horizontal structural complexity metric – crown height ($R^2 = 0.664$) and grid-level vertical metric – canopy cover ($R^2 = 0.583$). Comparisons of volumetric complexity metrics between the data acquisition approaches demonstrated the lowest correlation values of 0.395 and 0.036 for grid-level and object-level metrics, respectively (Figure 5). The highest rank agreement between metrics derived from heli-ALS and TLS were recorded for object-level horizontal structural complexity (crown height 0.795) and grid-level vertical complexity where crown height variability and canopy cover variability exhibited Spearman rank coefficients of 0.80 and 0.78, respectively.

Discussion

Laser scanning has been adopted as the foremost technique to characterize forest structural details and thus being an intriguing observation method for assessing vertical, horizontal, and volumetric complexity of forest stands (Seidel et al. 2019; Yrttimaa et al. 2020). Point clouds capable of characterizing the required level of detail can be captured from various platforms resulting in different data acquisition geometries which affect their abilities to characterize the forest structure

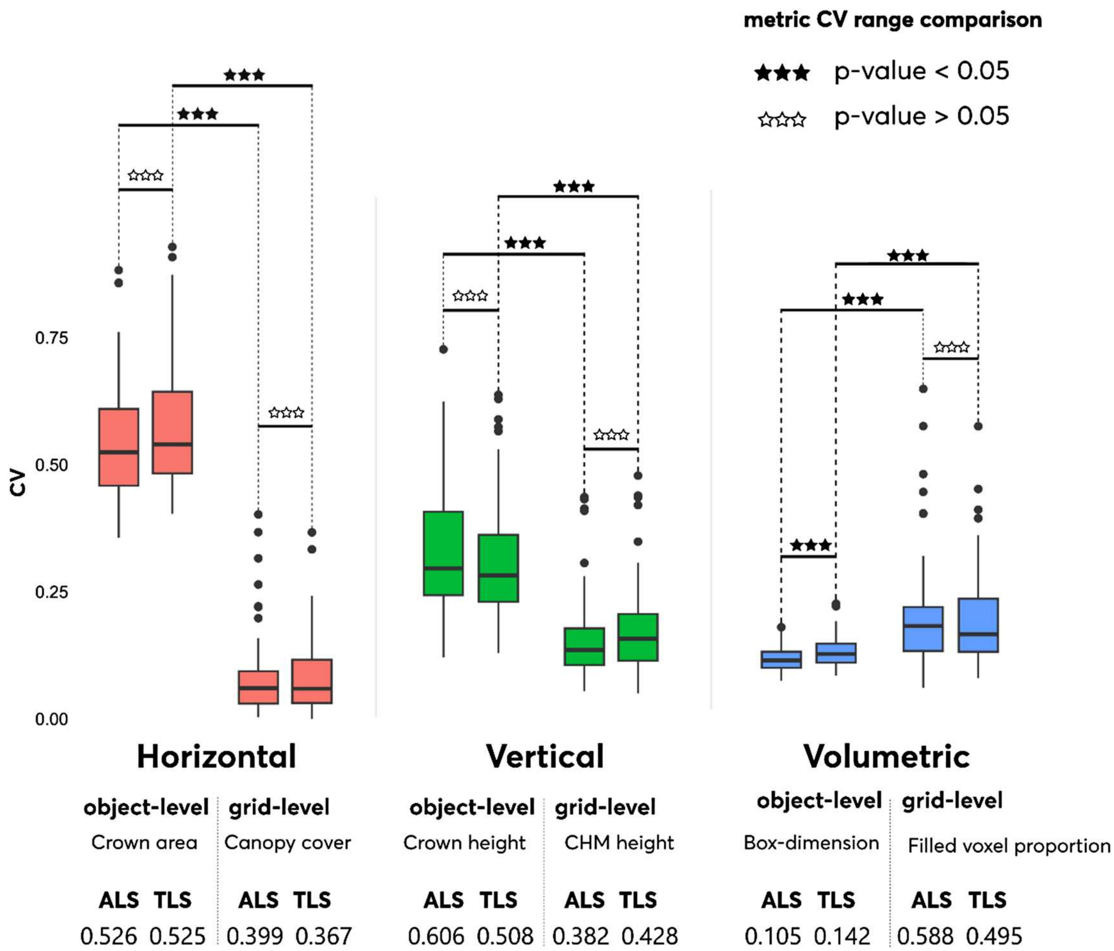

Figure 4. Comparison of the captured range of variability, measured as the coefficient of variation (CV), in horizontal, vertical, and volumetric structural complexity metrics calculated using object-level and grid-level approaches between helicopter-borne laser scanning (heli-ALS) and terrestrial laser scanning (TLS).

(Maltamo et al. 2014). In this study, we aimed to investigate if structural complexity of a forest stand can be characterized consistently in its different dimensions (i.e. horizontal, vertical, volumetric) using different laser scanning approaches. We thereby compared structural complexity assessment by analysing variability either in individual tree characteristics (i.e. the object-based approach) or canopy properties (i.e. the grid-level approach) using point cloud data captured either from above the forest with helicopter-borne heli-ALS or inside the canopy using TLS. We evaluated their capacities in capturing the range of structural complexity measures across sample plots and compared how well the obtained metrics aligned when derived using different analysis methods and data acquisition approaches. With a broader variability range captured, it could be easier to distinguish between forest stands and identify, e.g. biodiversity hotspots. Similarly, a greater association between TLS and heli-ALS would indicate the applicability potential of the presented methods across laser scanning methods, promoting their operational use.

Structural complexity metric range comparison

We hypothesized that heli-ALS could characterize a larger range in vertical structural complexity as it characterizes trees from above the canopy, allowing for a more comprehensive reconstruction of the top of the canopy, leading to more accurate tree height estimations. (Liang et al. 2019) concluded that this above-canopy measurement geometry has been the most suitable remote sensing technique to estimate tree height and might be even superior to field measurements based on clinometers (Jin et al. 2020; Y. Wang et al. 2019) especially when the stand structure is complex. The results obtained in this study partially approved H1 because heli-ALS did capture a broader range in vertical complexity using the object-level approach involving the analysis of individual tree height variability within the sample

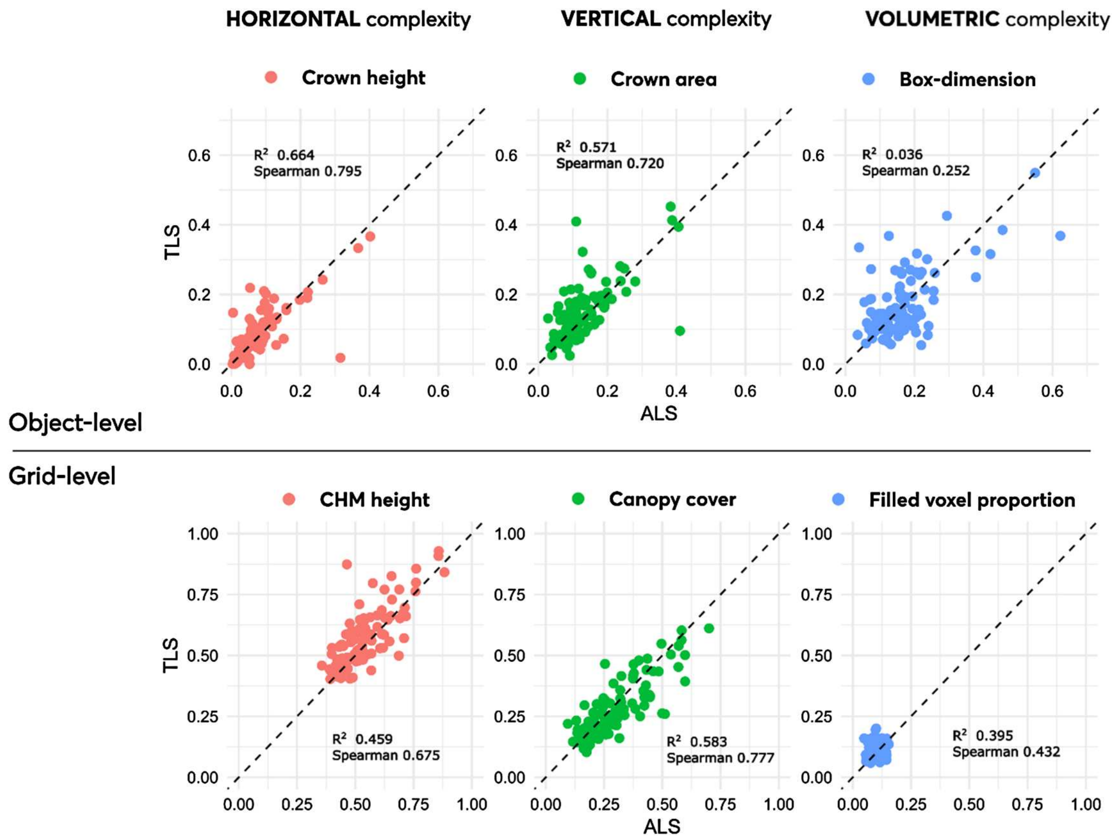

Figure 5. Vertical, horizontal and volumetric structural complexity metric agreement for object-level and grid-level approaches between helicopter-borne laser scanning (heli-ALS) and terrestrial laser scanning (TLS).

plots. Meanwhile, the grid-level approach showed the opposite likely due to TLS providing a more detailed reconstructions with less occlusions from the bottom part of tree crown compared to heli-ALS because of its below-canopy scanning geometry. However, the conducted F-tests did not provide statistical evidence for differences in the captured ranges, implying that the observed ranges in vertical complexity metrices were similar between the observation techniques.

We also hypothesized that TLS would be able to characterize a larger range in horizontal structural complexity, because related analysis were based on crown area and canopy cover variability. These metrics were expected to be estimated more reliably with under canopy laser scanning such as TLS (Pyorala et al. 2018). TLS point acquisition geometry allows obtaining more information about horizontal crown dimensions which is assumed to yield more detailed horizontal structural complexity estimations (Y. Wang and Fang 2020). The findings were contradicting H2 because the captured ranges were almost equal and thus not significant ($p >$ 0.05) between TLS and heli-ALS. This might be explained by the high detail of our heli-ALS point clouds that appeared to convey as sufficient data source as TLS for capturing variability in crown area or canopy cover. The applied metrics decreased the required level of detail in forest characterization so that the higher geometric accuracy of TLS was not fully employed, leading to similar metric outcomes between the two scanning methods.

It should be noted here that, as an alternative to crown area, it could have been possible to directly measure the stem diameter of the trees with both methods. The heli-ALS data used here has been proven to be feasible even for stem curve estimation (Hyyppä et al. 2022). However, we wanted to keep the analysis methods as straightforward as possible and applicable to different terrestrial and aerial point clouds as well. With both approaches – considering horizontal complexity based on variability in stem diameters or crown areas – the issue of under sampling can occur. This means that the stem diameter or crown area cannot be measured for all the trees present in the forest due to incomplete point cloud characterization. Under sampling takes place because vegetetion is blocking laser returns resulting in missed detection of smaller or supressed trees (Vastaranta et al. 2011; Iqbal et al. 2021).

In this study, volumetric structural complexity assessment was based on analysis of how the architectural complexity of individual trees varies within the sample plot (object-level) and how large a proportion of the space available is occupied by vegetative structures (grid-level). Due to its more detailed point cloud reconstruction capacity over heli-ALS, we hypothesized that TLS could capture a larger range in these metrics. The set hypothesis was confirmed when the object-level approach was used, where TLS captured a significantly ($p < 0.05$) broader range of variability in trees' box-dimensions across sample plots, while the grid-level approach resulted in a similar range captured regardless of the point cloud data used. These findings could be explained by the different data acquisition geometries and thus different point cloud reconstruction strategies. With more details reconstructed, TLS has the potential to characterize more complex tree architectures (Calders et al. 2020), likely to also capture greater variation in the derived object-level metric, the box-dimensions. Whereas in the grid-level approach, subsetting the investigated point clouds between 1 m above the ground and 80% of maximum height aimed to facilitate comparison between TLS and heli-ALS, where it seemingly succeeded in this respect. Vegetation occupancy comparison would have yielded different results without this subsetting, as both laser scanning techniques have their advantages and disadvantages especially in more dense forests with closed canopy conditions (Yrttimaa et al. 2024).

In addition to comparing the laser scanning methods, we also analyzed potential differences in structural complexity assessments between the analysis methods. According to our findings, the object-level approach could capture a broader range in the variability of horizontal and vertical forest structures while the grid-level approach seemed to provide more insights into volumetric complexity assessment. Regarding horizontal and vertical dimensions, the results were as hypothesized (H3). The object-level structural complexity metrics might be able to detect smaller and occluded trees and therefore capable of capturing larger range in complexity compared to the grid-level metrics based on CHMs. In the grid-level approach, the sample plot was divided into six 60-degree segments that were used to calculate CV of each investigated metric. This approach aimed to balance plot size, spatial resolution, and the ability to assess intra-plot structural variability. The use of larger segment proportions would reduce sensitivity to inter-plot metric variability (Smith and Urban 1988). Segment size and proportions must be revised for other forest types to improve metric variability assessments.

With the volumetric dimension, the capability of the grid-level approach to capture a broader range of variability may be explained by the different principles of how it aims to characterize structural complexity compared to the object-level approach. While the object-level approach for volumetric complexity assessment described the architectural variability of individual trees, the grid-level approach described variability in vegetation occupancy, assuming a higher degree of occupancy indicating a more complex stand. It seems that the architecture of individual trees varied by a lesser magnitude than vegetation occupancy did, potentially explaining the findings contradicting with H3. Considering the applicability of the approaches, the object-level approach could be more suitable to be used when detailed point cloud data is available because it is based on individual tree detection which is a very point cloud density dependent process (Weiser et al. 2022). The grid-level approach may be more suitable for lower density datasets better available for larger areas, compromising forest descriptive potential for analysis scalability (Holopainen et al. 2014; Kankare et al. 2017). The findings may also suggest that that the object-level approach should be prioritized over the grid-level approach if more distinct differences between the more complex and less complex forest stands are desired to be obtained.

Considering vertical, horizontal, and volumetric forest structural complexity metrics, it should be kept in mind that they are interconnected, as they are shaped by site conditions, underlying ecological processes and silvicultural operations that dictate the resource availability and distribution throughout the forest ecosystems (De Cáceres et al. 2019; Montoya-Sánchez et al. 2024). Vertical complexity describes the forest layering and light availability closely interacting with forest horizontal structural complexity due to allometric relationships – trees large in horizontal dimensions tend to feature large vertical dimensions as well, making respective variation interconnected (Hulshof et al. 2015). Volumetric complexity considers both horizontal and vertical dimensions, representing three-dimensional arrangement of vegetative structures within the forest and reflecting the overall effects of growth and competition (Malhi et al. 2018; Cimdins et al. 2024). Understanding the structural complexity metric assessment insights using different sensors and data processing approaches will help us to efficiently utilize the interplay between structural complexity metrics addressing certain forest management strategies (Camarretta et al. 2020).

Structural complexity metric correlation and agreement comparison

Previous studies have shown the capabilities of both heli-ALS and TLS to provide detailed information about forest structure, and therefore we presumed that there could be a strong agreement between structural complexity metrices derived from corresponding point cloud data (H4). Our results showed a coefficient of determination (R^2) ranging from 0.46 to 0.66 for horizontal and vertical structural complexity metrics, but an R^2 of 0.04 was obtained for object-level volumetric and 0.40 for grid-level volumetric metric. Spearman rank coefficient showed similar trends (Figure 5). These findings indicate the similar capacities of both TLS and heli-ALS in characterizing the two-dimensional complexity of a forest stand, which in this study was intentionally based on such characteristics that were expected to be rather well obtainable from both datasets. Previous studies have indicated similar intra-platform correlations between TLS and mobile laser scanning, both obtained using a similar, bottom-up measurement geometry from inside the forest canopy (Kacic et al. 2025). In this respect, our findings can be considered encouraging in that sense that they showed that heli-ALS could provide observations of structural complexity, at least from its vertical or horizontal components, that were somehow comparable to those obtained using TLS, thereby providing added value for structural complexity assessment through its enhanced feasibility for operational applications.

However, differences in the point cloud properties between heli-ALS and TLS were still obvious, and consequent differences were seen in the association with the obtained metrices. Computing the variability of individual tree box-dimensions and vegetation occupancy within a sample plot seemed to be more dependent on the measurement geometry that was different between TLS and heli-ALS. Thus, a relatively weak association between heli-ALS-derived and TLS-derived variability in box dimensions may be due to different data acquisition approaches – top-down of heli-ALS compared to bottom-up of TLS – and geometric accuracy and consequently captured architectural details. In case of vegetation occupancy analysis, subsetting the point cloud between 1 m and 80% height and using a 20-cm voxelization did not completely succeed in standardizing the data for aligned observations between the laser scanning methods, most probably due to different data acquisition geometries (Yrttimaa et al. 2024). Conversely, TLS measurements are limited by their ability to penetrate dense canopy and reach the upper branches thereby simplifying box-dimension architecture (Heidenreich and Seidel 2022).

Method considerations and potential advancements

Heli-ALS represents a cost-efficient alternative for TLS data to capture detailed reconstruction of forest structural characteristics, with a data acquisition campaign taking about one hour per hectare compared to 3–7 days per hectare of that of TLS (Terryn et al. 2022). However, it should be kept in mind that the quality of the acquired point cloud directly influences tree identification, segmentation, and characterization accuracy (Krisanski et al. 2021; (Hyyppä et al. 2022)) which is fundamental for object-level estimations as used in this study. Factors other than the measurement geometry and related details, such as ranging and positioning errors could have affected the obtained findings (Ren et al. 2016). It should be noted that the TLS was collected during late April to late May while heli-ALS data acquisition took place in mid-June, meaning a mixture of leaf-off and leaf-on conditions. Although the study sites were dominated by conifers, there were also a few deciduous trees-dominated plots involved which could have been affected by the absence of leaves during the TLS campaign as well as their presence during the heli-ALS data acquisitions. While we aimed to use metrics that should be rather invariant for the change in phenological conditions, it could have affected the results by making the TLS-based and heli-ALS-based observations deviate from each other more than they would have with more synchronized data acquisition. It is known that the presence of leaves affects laser pulse penetration capacity and thus influences canopy cover and forest gap estimation. For crown area and box-dimension estimation of broad-leaved trees this could have influenced. Although the grid-level analyses were carried out at a resolution of 0.2 m (voxel occupancy) and 0.5 m (CHM), the influence of phenology in the observed differences between TLS and heli-ALS cannot be fully neglected.

The experiments showed that, when the aim is to obtain comparable observations of forest structural complexity using different observation techniques, it is essential to select appropriate metrics that consider both data properties and analysis methods used. For example, detecting individual trees is usually challenging in dense, multilayered forests, making the grid-based approach a viable alternative for the object-based approach that would otherwise yield more reasonable observations. The same applies when lower-resolution data is used. We acknowledge that point cloud-based and raster-based methods are different from data structures perspective (Jakubowski et al. 2013). The point cloud data used in this study, particularly TLS, facilitates more sophisticated methods for assessing forest structural complexity (M. Wang et al. 2024) and conversion of such detailed point cloud data into raster-based formats, as applied in the grid-level approach, results in some loss of data descriptive potential. Nevertheless, the aim of this study was to define and calculate vertical, horizontal, and volumetric structural complexity metrics and understand their variability introduced by object and grid-level analytical approaches. A true challenge is therefore to find an appropriate set of metrics that simplify the detailed point cloud reconstructions of trees and tree communities sufficiently enough, to enable inter-platform comparison without losing necessary details that eventually distinguish a more complex stand from a less complex stand. Kacic et al. (2025) showed that, even with an otherwise comparable data acquisition geometry, the structural complexity metrics from TLS and mobile laser scanning did not perfectly align with each other. In this study, the use of ground-based and airborne datasets extended this challenge even more. Still, the findings obtained here highlight the prospects of heli-ALS to be used as an alternative to TLS for obtaining detailed characterization of tree communities for the evaluation of their structural complexity.

Overall, our findings provide insights into the prospective capability of heli-ALS for estimating structural complexity and facilitate comparisons with TLS. This study could be continued to understand how structural complexity is developing over time. Structural complexity metrics analysis results could be used to scale up ALS based national level forest structural complexity mapping and hotspot modeling. Previous studies have demonstrated the ALS and TLS fusion importance for structural parameter estimation (Terryn et al. 2022). The integration of heli-ALS and TLS data may offer advantages for more accurate structural complexity modeling, direct tree measurements, and the detection of top branches, but that would require extra resources to collect such dataset over large areas and for operational use. The influence of the used point cloud data type and the adopted analysis methods seemingly have an influence on the structural complexity estimates, which should be kept in mind when planning time series data acquisitions and related analysis. Structural complexity metric extrapolation to larger areas over different forest types may be feasible using more time- and cost-efficient, plane-based lower-density ALS (e.g. 0.5 pts/m^2). However, this approach requires further investigation, as reduced point density can limit the accurate characterization of understory vegetation. For broader applicability, it is important to select metrics that are more robust to variations in point cloud density and scanning geometry, such as canopy gap fraction and canopy entropy (Cimdins et al. 2025). Our findings highlight that object-level LiDAR assessments provide high spatial detail and versatility for structural complexity estimations compared to grid-level approaches. This study also shows that helicopter-borne ALS and TLS scanning methods do not produce statistically significant differences in structural complexity metrics when the ALS point clouds are sufficiently detailed, indicating that method choice can be driven by study goals and resource constraints. We note, however, that TLS currently offers advantages for nature conservation applications, as its high point density and ground-level perspective capture fine-scale structural details – such as understory complexity and microhabitats – that are critical for habitat assessments (Wardius and Hein 2024). In contrast, detailed ALS acquisitions may be more cost-effective for large-scale commercial timber inventories, especially when fine plot-level detail is not essential (White et al. 2025).

Conclusion

The results of this study highlight that identifying individual trees (object-level) and quantifying variability in their characteristics can capture a broader range in variation in structural complexity of forests and therefore these approaches should be prioritized in structural complexity assessments. However, volumetric structural estimations range was larger for grid-level estimation (filled voxel proportion) using both heli-ALS and TLS compared to object level estimation (box-dimension). Heli-ALS and TLS did not yield statistically significant differences ($p < 0.05$) in structural estimation ranges, except box-dimensions. Thus, when assessing two-dimensional structural complexity, heli-ALS seems to convey as sufficient observations as TLS. Vertical and horizontal two-dimensional object and grid-level structural complexity metrics had stronger agreement between heli-ALS and TLS data compared to volumetric estimations. This study gives practical insights that heli-ALS is suitable data acquisition method for landscape-level forest structural complexity assessments, but TLS remains superior in detailed volumetric tree level analysis in dense structurally complex forests. Study underlines the structural complexity assessment data collection and processing approaches which needs to be considered and optimized for successful decision-making in forest conservation and management.

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Data availability statement

The data underlying this article will be shared on reasonable request to the corresponding author.

References

Calders K, Adams J, Armston J, Bartholomeus H, Bauwens S, Bentley LP, Chave J, Danson FM, Demol M, Disney M, et al. 2020. Terrestrial laser scanning in forest ecology: expanding the horizon. Remote Sens Environ. 251:112102. doi:10.1016/j.rse.2020.112102.

Camarretta N, Harrison PA, Bailey T, Potts B, Lucieer A, Davidson N, Hunt M. 2020. Monitoring forest structure to guide adaptive management of forest restoration: a review of remote sensing approaches. New For. 51(4):573–596. doi:10.1007/s11056-019-09754-5.

Campbell MJ, Dennison PE, Hudak AT, Parham LM, Butler BW. 2018. Quantifying understory vegetation density using small-footprint airborne lidar. Remote Sens Environ. 215:330–342. doi:10.1016/j.rse.2018.06.023.

Carrasco L, Giam X, Papeş M, Sheldon KS. 2019. Metrics of lidar-derived 3D vegetation structure reveal contrasting effects of horizontal and vertical forest heterogeneity on bird species richness. Remote Sens (Basel). 11(7):743. doi:10.3390/rs11070743.

Cimdins R, Yrttimaa T, Hyyppä J, Vastaranta M, Kankare V. 2024. Quantifying changes in forest structural complexity using bi-temporal airborne laser scanning. Europ J Remot Sens. 57 (1):2417905. doi:10.1080/22797254.2024.2417905.

Cimdins R, Yrttimaa T, Hyyppä J, Vastaranta M, Kankare V. 2025. Capturing trends in forest structural complexity development using laser scanning techniques. Trees, For Peop. 21:100954. doi:10.1016/j.tfp.2025.100954.

Dalponte M, Coomes DA. 2016. Tree-centric mapping of forest carbon density from airborne laser scanning and hyperspectral data. Meth Ecol Evol. 7(10):1236–1245. doi:10.1111/2041-210X.12575.

De Cáceres M, Martín-Alcón S, González-Olabarria JR, Coll L. 2019. A general method for the classification of forest stands using species composition and vertical and horizontal structure. Ann For Sci. 76(40):1–19. doi:10.1007/s13595-019-0824-0.

European Commission. 2021. *New EU forest strategy for* 2030.

Fahey RT, Fotis AT, Woods KD. 2015. Quantifying canopy complexity and effects on productivity and resilience in late-successional hemlock–hardwood forests. Ecol Appl. 25(3):834–847. doi:10.1890/14-1012.1.

Franklin Jerry F, Van Pelt R. 2004. Spatial aspects of structural complexity in old-growth forests. J Forest. 102(3):22–28. doi:10.1093/jof/102.3.22.

Fuhr M, Lalechère E, Monnet JM, Bergès L. 2022. Detecting overmature forests with airborne laser scanning (ALS). Remote Sens Ecol Conserv. 8(5):731–743. doi:10.1002/rse2.274

Hamraz H, Contreras MA, Zhang J. 2017. Forest understory trees can be segmented accurately within sufficiently dense airborne laser scanning point clouds. Sci Rep. 7(1):6770. doi:10.1038/s41598-017-07200-0.

Heidenreich MG, Seidel D. 2022. Assessing forest vitality and forest structure using 3D data: a case study from the Hainich National Park, Germany. Front Fores Glob Chang 5:929106. doi:10.3389/ffgc.2022.929106.

Holopainen M, Vastaranta M, Hyyppä J. 2014. Outlook for the next generation's precision forestry in Finland. Forests. 5(7):1682–1694. doi:10.3390/f5071682.

Hulshof CM, Swenson NG, Weiser MD. 2015. Tree height-diameter allometry across the United States. Ecol Evol. 5(6):1193–1204. doi:10.1002/ece3.1328.

Huuskonen S, Domisch T, Finér L, Hantula J, Hynynen J, Matala J, Miina J, Neuvonen S, Nevalainen S, Niemistö P, et al. 2021. What is the potential for replacing monocultures with mixed-species stands to enhance ecosystem services in boreal forests in Fennoscandia? For Ecol Manag. 479:118558. doi:10.1016/j.foreco.2020.118558.

Hynynen J, Ahtikoski A, Siitonen J, Sievänen R, Liski J. 2005. Applying the MOTTI simulator to analyse the effects of alternative management schedules on timber and non-timber production. For Ecol Manag. 207(1-2 SPEC. ISS.):5–18. doi:10.1016/j.foreco.2004.10.015.

Hyyppä E, Kukko A, Kaartinen H, Yu X, Muhojoki J, Hakala T, Hyyppä J. 2022. Direct and automatic measurements of stem curve and volume using a high-resolution airborne laser scanning system. Sci Rem Sens. 5:100050. doi:10.1016/j.srs.2022.100050.

Iqbal IA, Osborn J, Stone C, Lucieer A. 2021. A comparison of als and dense photogrammetric point clouds for individual tree detection in radiata pine plantations. Remote Sens (Basel). 13(17):3536. doi:10.3390/rs13173536.

Jakubowski MK, Li W, Guo Q, Kelly M. 2013. Delineating individual trees from lidar data: A comparison of vector- and raster-based segmentation approaches. Remote Sens (Basel). 5(9):4163–4186. doi:10.3390/rs5094163.

Jin C, Oh Cy, Shin S, Njungwi NW, Choi C. 2020. A comparative study to evaluate accuracy on canopy height and density using UAV, ALS, and fieldwork. Forests. 11(2):241. doi:10.3390/f11020241.

Juchheim J, Ammer C, Schall P, Seidel D. 2017. Canopy space filling rather than conventional measures of structural diversity explains productivity of beech stands. For Ecol Manag. 395:19–26. doi:10.1016/j.foreco.2017.03.036.

Kaartinen H, Hyyppä J, Yu X, Vastaranta M, Hyyppä H, Kukko A, Holopainen M, Heipke C, Hirschmugl M, Morsdorf F, *et al.* 2012. An international comparison of individual tree detection and extraction using airborne laser scanning. Remote Sens. 4(4):950–974. doi:10.3390/rs4040950.

Kacic P, Gessner U, Hakkenberg CR, Holzwarth S, Müller J, Pierick K, Seidel D, Thonfeld F, Torresani M, Kuenzer C. 2025. Characterizing local forest structural complexity based on multi-platform and -sensor derived indicators. Ecol Indic. 170:113085. doi:10.1016/j.ecolind.2025.113085.

Kankare V, Holopainen M, Vastaranta M, Liang X, Yu X, Kaartinen H, Kukko A, Hyyppä J. 2017. Lecture notes in geoinformation and cartography. Lect Not Geoinform Cart. 183–195. doi:10.1007/978-3-319-45123-7_14.

Kankare V, Vauhkonen J, Tanhuanpää T, Holopainen M, Vastaranta M, Joensuu M, Krooks A, Hyyppä J, Hyyppä H, Alho P, Viitala R. 2014. Accuracy in estimation of timber assortments and stem distribution - a comparison of airborne and terrestrial laser scanning techniques. ISPRS J Photogramm Remote Sens. 97:89–97. doi:10.1016/j.isprsjprs.2014.08.008.

Krisanski S, Taskhiri MS, Aracil SG, Herries D, Turner P. 2021. Sensor agnostic semantic segmentation of structurally diverse and complex forest point clouds using deep learning. Remote Sens (Basel). 13(8):1413. doi:10.3390/rs13081413.

LaRue EA, Fahey RT, Alveshere BC, Atkins JW, Bhatt P, Buma B, Chen A, Cousins S, Elliott JM, Elmore AJ, … Fei S. 2023. A theoretical framework for the ecological role of three-dimensional structural diversity. Front Ecol Environ. 21(1):4–13. doi:10.1002/fee.2587.

Lecigne B, Delagrange S, Messier C. 2018. Exploring trees in three dimensions: VoxR, a novel voxel-based R package dedicated to analysing the complex arrangement of tree crowns. Ann Bot. 121(4):589–601. doi:10.1093/aob/mcx095.

Liang X, Wang Y, Pyörälä J, Lehtomäki M, Yu X, Kaartinen H, Kukko A, Honkavaara E, Issaoui AEI, Nevalainen O, et al. 2019. Forest in situ observations using unmanned aerial vehicle as an alternative of terrestrial measurements. For Ecosyst. 6(1). doi:10.1186/s40663-019-0173-3.

Liu G, Wang J, Dong P, Chen Y, Liu Z. 2018. Estimating individual tree height and diameter at breast height (DBH) from terrestrial laser scanning (TLS) data at plot level. Forests. 9(2):398. doi:10.3390/f9070398.

Malhi Y, Jackson T, Bentley LP, Lau A, Shenkin A, Herold M, Calders K, Bartholomeus H, Disney MI. 2018. New perspectives on the ecology of tree structure and tree communities through terrestrial laser scanning. Interface Focus. 8(2):20170052. doi:10.1098/rsfs.2017.0052.

Maltamo M, Naesset E, Vauhkonen J. 2014. *Managing forest ecosystems forestry applications of airborne laser scanning concepts and case studies* (Vol. 27). Heidelberg.: Springer Dordrecht. doi:10.1007/978-94-017-8663-8.

McElhinny C, Gibbons P, Brack C, Bauhus J. 2005. Forest and woodland stand structural complexity: its definition and measurement. For Ecol Manag. 218(1–3):1–24. doi:10.1016/j.foreco.2005.08.034.

Montoya-Sánchez V, Camarretta N, Ehbrecht M, Schlund M, Brant Paterno G, Seidel D, Guerrero-Ramírez N, Brambach F, Hölscher D, Kreft H, et al. 2024. Comparing airborne and terrestrial LiDAR with ground-based inventory metrics of vegetation structural complexity in oil palm agroforests. Ecol Indic. 166:112306. doi:10.1016/j.ecolind.2024.112306.

Neudam LC, Höwler K, Seidel D. 2023. Stem shape and structural complexity change in beech forests along a management gradient. For Ecol Manag. 549:121473. doi:10.1016/j.foreco.2023.121473.

Okojie JA, Okojie LO, Effiom AE, Odia BE. 2020. Relative canopy height modelling precision from UAV and ALS datasets for forest tree height estimation. Rem Sens Appl: Soc Environ. 17:100284. doi:10.1016/j.rsase.2019.100284.

Pascual A. 2019. Using tree detection based on airborne laser scanning to improve forest inventory considering edge effects and the co-registration factor. Remote Sens (Basel). 11(22):2675. doi:10.3390/rs11222675.

Persson HJ, Olofsson K, Holmgren J. 2022. Two-phase forest inventory using very-high-resolution laser scanning. Remote Sens Environ. 271:112909. doi:10.1016/j.rse.2022.112909.

Peuhkurinen J, Mehtätalo L, Maltamo M. 2011. Comparing individual tree detection and the areabased statistical approach for the retrieval of forest stand characteristics using airborne laser scanning in Scots pine stands. Can J For Res. 41(3):583–598. doi:10.1139/X10-223.

Popescu SC, Wynne RH. 2004. Seeing the trees in the forest. Photogrammetric Engineering & Remote Sensing. 70(5):589–604. doi:10.14358/PERS.70.5.589.

Pyorala J, Liang X, Vastaranta M, Saarinen N, Kankare V, Wang Y, Holopainen M, Hyyppa J. 2018. Quantitative assessment of scots pine (Pinus SylvestrisL.) Whorl structure in a forest environment using terrestrial laser scanning. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 11(10):3598–3607. doi:10.1109/JSTARS.2018.2819598.

Ren HC, Yan Q, Liu ZJ, Zuo ZQ, Xu QQ, Li FF, Song C. 2016. Study on analysis from sources of error for Airborne LIDAR. IOP Conference Series: Earth and Environmental Science. 46(1):012030. doi:10.1088/1755-1315/46/1/012030.

Ross CW, Loudermilk EL, Skowronski N, Pokswinski S, Hiers JK, O'brien J. 2022. LiDAR voxel-size optimization for canopy gap estimation. Remote Sens (Basel). 14(5):1054. doi:10.3390/rs14051054.

Seidel D. 2018. A holistic approach to determine tree structural complexity based on laser scanning data and fractal analysis. Ecol Evol. 8(1):128–134. doi:10.1002/ece3.3661.

Seidel D, Ammer C. 2023. Towards a causal understanding of the relationship between structural complexity, productivity, and adaptability of forests based on principles of thermodynamics. For Ecol Manag. 544:121238. doi:10.1016/j.foreco.2023.121238.

Seidel D, Ehbrecht M, Annighöfer P, Ammer C. 2019. From tree to stand-level structural complexity — Which properties make a forest stand complex? Agric For Meteorol. 278:107699. doi:10.1016/j.agrformet.2019.107699.

Shugart HH, Saatchi S, Hall FG. 2010. Importance of structure and its measurement in quantifying function of forest ecosystems. J Geophys Res Biogeosci. 115(4):G00E13. doi:10.1029/2009JG000993.

Smith TM, Urban DL. 1988. Scale and resolution of forest structural pattern. Vegetatio. 74:143–150. doi:10.1007/BF00044739.

Srinivasan S, Popescu SC, Eriksson M, Sheridan RD, Ku NW. 2015. Terrestrial laser scanning as an effective tool to retrieve tree level height, crown width, and stem diameter. Remote Sens (Basel). 7(2):1877–1896. doi:10.3390/rs70201877.

Sverdrup-Thygeson A, Ørka HO, Gobakken T, Næsset E. 2016. Can airborne laser scanning assist in mapping and monitoring natural forests? For Ecol Manag. 369:116–125. doi:10.1016/j.foreco.2016.03.035.

Terryn L, Calders K, Bartholomeus H, Bartolo RE, Brede B, D'hont B, Disney M, Herold M, Lau A, Shenkin A, et al. 2022. Quantifying tropical forest structure through terrestrial and UAV laser scanning fusion in Australian rainforests. Remote Sens Environ. 271:112912. doi:10.1016/j.rse.2022.112912.

Torresan C, Strunk J, Zald HSJ, Zhiqiang Y, Cohen WB. 2014. Comparing statistical techniques to classify the structure of mountain forest stands using CHM-derived metrics in

Trento province (Italy). Euro J Rem Sens. 47(1):75–94. doi:10.5721/EuJRS20144706.

Vastaranta M, Holopainen M, Yu X, Hyyppä J, Mäkinen A, Rasinmäki J, Melkas T, Kaartinen H, Hyyppä H. 2011. Effects of individual tree detection error sources on forest management planning calculations. Remote Sens (Basel). 3(8):1614–1626. doi:10.3390/rs3081614.

Vastaranta M, Wulder MA, White JC, Pekkarinen A, Tuominen S, Ginzler C, Kankare V, Holopainen M, Hyyppä J, Hyyppä H. 2013. Airborne laser scanning and digital stereo imagery measures of forest structure: Comparative results and implications to forest mapping and inventory update. Can J Remote Sens. 39(5):382–395. doi:10.5589/m13-046.

Vehmas M, Packalén P, Maltamo M, Eerikäinen K. 2011. Using airborne laser scanning data for detecting canopy gaps and their understory type in mature boreal forest. Ann For Sci. 68(4):825–835. doi:10.1007/s13595-011-0079-x.

Venier LA, Swystun T, Mazerolle MJ, Kreutzweiser DP, Wainio-Keizer KL, McIlwrick KA, Woods ME, Wang X. 2019. Modelling vegetation understory cover using LiDAR metrics. PLoS One. 14(11):e0220096. doi:10.1371/journal.pone.0220096.

Wang M, Calders K, Verbeeck H, Verheyen K, Baeten L, Blondeel H, Muys B, Ponette Q, Armston J, Van Coillie F. 2024. Exploring the influence of tree species richness on vertical structure variability in young plantations using terrestrial laser scanning. For Ecol Manag. 554:121662. doi:10.1016/j.foreco.2023.121662.

Wang Y, Fang H. 2020. Estimation of LAI with the LiDAR technology: a review. Remote Sens (Basel). 12(20):3457–3428. doi:10.3390/rs12203457.

Wang Y, Lehtomäki M, Liang X, Pyörälä J, Kukko A, Jaakkola A, Liu J, Feng Z, Chen R, Hyyppä J. 2019. Is field-measured tree height as reliable as believed – a comparison study of tree height estimates from field measurement, airborne laser scanning and terrestrial laser scanning in a boreal forest. ISPRS J Photogramm Remote Sens. 147:132–145. doi:10.1016/j.isprsjprs.2018.11.008.

Wardius Y, Hein S. 2024. Terrestrial laser scanning vs. manual methods for assessing complex forest stand structure: a comparative analysis on plenter forests. Eur J For Res. 143(2):635–649. doi:10.1007/s10342-023-01641-1.

Weiser H, Schäfer J, Winiwarter L, Krašovec N, Fassnacht FE, Höfle B. 2022. Individual tree point clouds and tree measurements from multi-platform laser scanning in German forests. Earth Syst Sci Data. 14(7):2989–3012. doi:10.5194/essd-14-2989-2022.

White JC, Tompalski P, Bater CW, Wulder MA, Fortin M, Hennigar C, Robere-Mcgugan G, Sinclair I, White R. 2025. Enhanced forest inventories in Canada: implementation, status, and research needs. Can J For Res. 55:1–37. doi:10.1139/cjfr-2024-0255.

Yrttimaa T, Luoma V, Saarinen N, Kankare V, Junttila S, Holopainen M, Hyyppä J, Vastaranta M. 2020. Structural changes in Boreal forests can be quantified using terrestrial laser scanning. Remote Sens (Basel). 12(17):2672. doi:10.3390/RS12172672.

Yrttimaa T, Matsuzaki S, Kankare V, Junttila S, Saarinen N, Kukko A, Hyyppä J, Miura J, Vastaranta M. 2024. Assessing Forest Traversability for Autonomous Mobile Systems Using CloseRange Airborne Laser Scanning. Croat J For Eng. 45(1):169–182. doi:10.5552/crojfe.2024.2229.

Yu X, Hyyppä J, Karjalainen M, Nurminen K, Karila K, Vastaranta M, Kankare V, Kaartinen H, Holopainen M, Honkavaara E, *et al*. 2015. Comparison of laser and stereo optical, SAR and InSAR point clouds from air- and space-borne sources in the retrieval of forest inventory attributes. Remote Sens, 7(12):15933–15954. doi:10.3390/rs71215809

Zenner EK. 2016. Differential growth response to increasing growing stock and structural complexity in even- and uneven-sized mixedPicea abiesstands in southern Finland. Can J For Res. 46(10):1195–1204. doi:10.1139/cjfr-2015-0400.