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Capturing trends in forest structural complexity development using laser scanning techniques

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ABSTRACT

Forest structural complexity reflects realized niche occupancy, capturing how effectively the vegetation utilizes available resources and provides habitats for species. This makes it a key indicator of forest ecosystem diversity, and an important characteristic to be monitored to facilitate sustainable forest management and conservation planning. Laser scanning has been recognized as a feasible technology for the characterization of heterogeneity in forest structure, reflecting its structural complexity. However, less is known about the capability of different laser scanning techniques to capture structural complexity development through time, and whether the cross-use of various data types and analysis methods yields consistent observations of the development. We aim to address this knowledge gap by investigating the capability of different laser scanning techniques to assess forest structural complexity development and evaluate whether comparable observations can be obtained regardless of the laser scanning technology used. The experiments were conducted across 49 sample plots within southern boreal forests in Evo, Finland. A 7–10-year monitoring period was captured using terrestrial laser scanning (TLS), and airborne laser scanning (ALS) at three different resolutions representing low (0.4-1 pts/m^2), medium (15-28 pts/m^2), and high (200-3600 pts/m^2) point densities. Eight metrics were used for structural complexity characterization: mean canopy height, canopy rugosity, gap fraction, vegetation occupancy, vertical evenness (Shannon entropy), variability in crown area and tree height, and mean fractal dimensions (box-dimension) among trees. Comparison of observations of structural complexity development showed that gap fraction and Shannon entropy exhibited consistent development directions and similar metric change magnitudes across all the investigated laser scanning techniques. In contrast, metrics characterizing three-dimensional complexity, such as vegetation occupancy and mean box-dimension, were more sensitive to point cloud data characteristics. These findings provide insights into selecting appropriate laser scanning techniques and analysis methods to monitor forest structural complexity development for applications such as conservation planning.

Introduction

Forest structural complexity is widely recognized as a key driver for the presence of high species richness (Stein et al., 2014). A larger number of species can coexist in more heterogeneous environments due to the increased availability of microhabitats (Zheng et al., 2024). Forest structural complexity also enhances forest resilience and ecosystem stability (Ishii et al., 2004), providing both economic and ecological benefits. Policymakers are increasingly advocating close-to-nature forest management practices that promote greater structural complexity. However, these processes must be planned and monitored. Nevertheless, unified standards for assessing forest structural complexity have yet to be established.

Structural diversity, or complexity, can be assessed by measuring the variability of vegetation characteristics per unit area (Lefsky et al., 2002). Variability in tree characteristics can be assessed based on conventional field inventory techniques, such as using clinometers for measuring tree heights and callipers for measuring tree diameters. These

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measurements have been used to calculate various indices quantifying structural complexity (Pommerening, 2002). The Shannon index, mingling index, diameter differentiation index, and Lorenz curve are widely used to assess forest diversity and structural complexity (Keren et al., 2020; Valbuena et al., 2013; Zhang et al., 2024). However, these conventional measurements can only cover relatively small areas, such as sample plots, and even from sample plots simple measurement tools do not provide detailed information about tree canopy architecture and vegetation spatial composition (McElhinny et al., 2005).

Remote sensing, particularly laser scanning techniques employing light detection and ranging (LiDAR), enables three-dimensional characterization of forest structural characteristics even over landscapes (White et al., 2016). Laser scanning measures the distance between the sensor and objects of interest by emitting laser pulses and timing how long it takes for them to return and converts the range measurements into a point cloud data (Wehr and Lohr, 1999). When used to characterize forests, laser scanning measurements capture details about canopy height and density, enabling characterization of individual tree characteristics and their variability within an area of interest (Maltamo et al., 2006; Næsset, 2009). The characterization capabilities of a laser scanning systems depend on data resolution which is generally determined by the sensor and platform properties; laser scanning point clouds can be generated from ground-based or low-altitude systems for close-range analysis, as well as high-altitude airborne or spaceborne laser scanning systems (Aalto et al., 2023; Dubayah et al., 2022; Kacic et al., 2025; LaRue et al., 2023; Martin and Valeria, 2022; White et al., 2016). For assessing forest structural complexity through the heterogeneity in vegetative structures, laser scanning offers significant advantages over conventional field surveys, including greater time and cost efficiency and the ability to capture fine-scale structural details (Atkins et al., 2023; Kane et al., 2010; Lefsky et al., 2002; Liu et al., 2022). As a ground-based system, terrestrial laser scanning (TLS) allows measuring individual trees at the level of stem, branches, and leaves (e.g. Calders et al., 2020; Liang et al., 2018). TLS provides an inner-canopy reconstruction geometry for measuring tree characteristics, enabling monitoring the development of forest stand structural characteristics that would otherwise be impossible or too labor-intensive to be monitored non-invasively using conventional field measurement methods (Calders et al., 2020; D'hont et al., 2024; Peng et al., 2025; Terryn et al., 2020, 2023; Willim et al., 2022; Yrttimaa et al., 2020). However, self-occlusion by the trees themselves often results in an incomplete reconstruction of the monitored forest environment (Abegg et al., 2017). Thus, the applied data acquisition setup, including the number and positioning of individual scan locations may affect the capacity of TLS to capture growth-induced structural changes (Li et al., 2021). An alternative is mobile laser scanning (MLS) where detailed point cloud reconstruction rather similar to that of TLS, although with slightly decreased geometric accuracy, is produced on-the-move using a kinematic platform such as a backpack or a vehicle, enhancing data acquisition efficiency (Balenović et al., 2020). Airborne laser scanning (ALS), on the other hand, provides a way to capture detailed structural complexity data from above the canopy over larger areas compared to TLS (Næsset, 2004). ALS point cloud properties can vary because the point cloud characteristics change at different flight speeds, altitudes, scanning angles, sensor combinations and properties (Keränen et al., 2016). Compared to TLS, ALS maintains a more homogenous point sampling pattern with the top-down measurement geometry, providing more consistent yet less detailed point cloud reconstructions of individual trees (Wang et al., 2019).

The level of detail captured by the point cloud data determines which analytical methods are appropriate to be used for forest structural complexity assessment. For instance, to evaluate the variability of the shape of individual tree stem or branch structures, small footprint data with a density of 1 400+ pts/m^2 is required (Corte et al., 2020). For a more generalized characterization of the variability in tree crown dimensions, a density of $>$ 10 pts/m^2 may be necessary (Kaartinen et al., 2012). To conduct sample plot-level analyses of vegetation occupancy and estimate canopy height and density variations, as low as 0.5 pts/m^2 may be adequate (Lim et al., 2010; Magnusson et al., 2007). Understanding how different point densities and observation geometries affect the retrieval of metrics characterizing forest structural complexity is crucial for effective use of point cloud data to monitor whether the forest stands are developing towards greater heterogeneity or homogeneity. Since laser scanning technology is evolving rapidly compared to typical forest inventory intervals of 5 to 10 years, it is likely that data from different sensor generations will need to be combined for long-term forest monitoring. Therefore, it is essential to identifying metrics that are least affected by sensor type, point cloud density, and data collection geometry. As an attempt to ensure consistency in observations when evaluating changes in forest structural metrics, using data acquisition configurations as similar as possible at both the beginning and end of the monitoring period may be necessary. An alternative approach could be to standardize the resolution and the scale of the observations, using e.g. voxelization. Two identical data acquisition campaigns can still produce slightly different point cloud reconstructions of the objects or areas of interest, making it difficult to distinguish between structural changes and those originating from differences in observation techniques. More specifically, the extent to which the point cloud characteristics influence the ability of different laser scanning technologies to capture trends in forest structural complexity over time has still remained uncertain.

This study aims to investigate how consistently forest structural complexity development can be captured over a 7–10-year period in Southern boreal forests using low-, medium-, and high-density ALS data as alternatives for TLS data. As an attempt to find a sensor-agnostic approach for forest structural complexity assessment, we use different analysis methods to characterize forest structural complexity as intra-plot variability in canopy height models (CHMs), individual tree characteristics, or point cloud distributions. We compare whether observations of structural complexity development, derived from different laser scanning techniques using various analysis methods, are consistent in terms of 1) the significance of the observed change, 2) the direction of the observed change, and 3) the magnitude of the observed change. Additionally, we assess the ecological plausibility of the investigated approaches by examining whether different analysis methods and laser scanning techniques yield similar outcomes of forest structural complexity development (i.e., development towards greater structural heterogeneity or homogeneity). The experiment is partitioned into two parts to provide insights into 1) how the chosen analysis method affects observations of structural complexity development when using the same laser scanning technique, and 2) how the chosen laser scanning technique affects the observations when analysed using the same methodology.

Materials and methods

Experimental design

The study site was located in Evo, Finland (61°11′48.87"N, 25°6′27.9"E), and comprised 49 circular plots (radius = 15 m) where no silvicultural management took place during the monitoring period from 2009 to 2021. The plots represent typical conditions of the southern boreal forest, varying from single-species to mixed-species compositions. The dominant tree species include Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) H. Karst.), Silver birch (*Betula pendula* Roth), and European aspen (*Populus tremula* L.). Each laser scanning dataset was acquired at two time points—at the beginning and end of this period (Fig. 1). The sample plots were initially established to cover the variation in different forest structures within the research site (Yu et al., 2015). A grid (32 m × 32 m) was then overlaid on the area, and 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 full range of variation in canopy

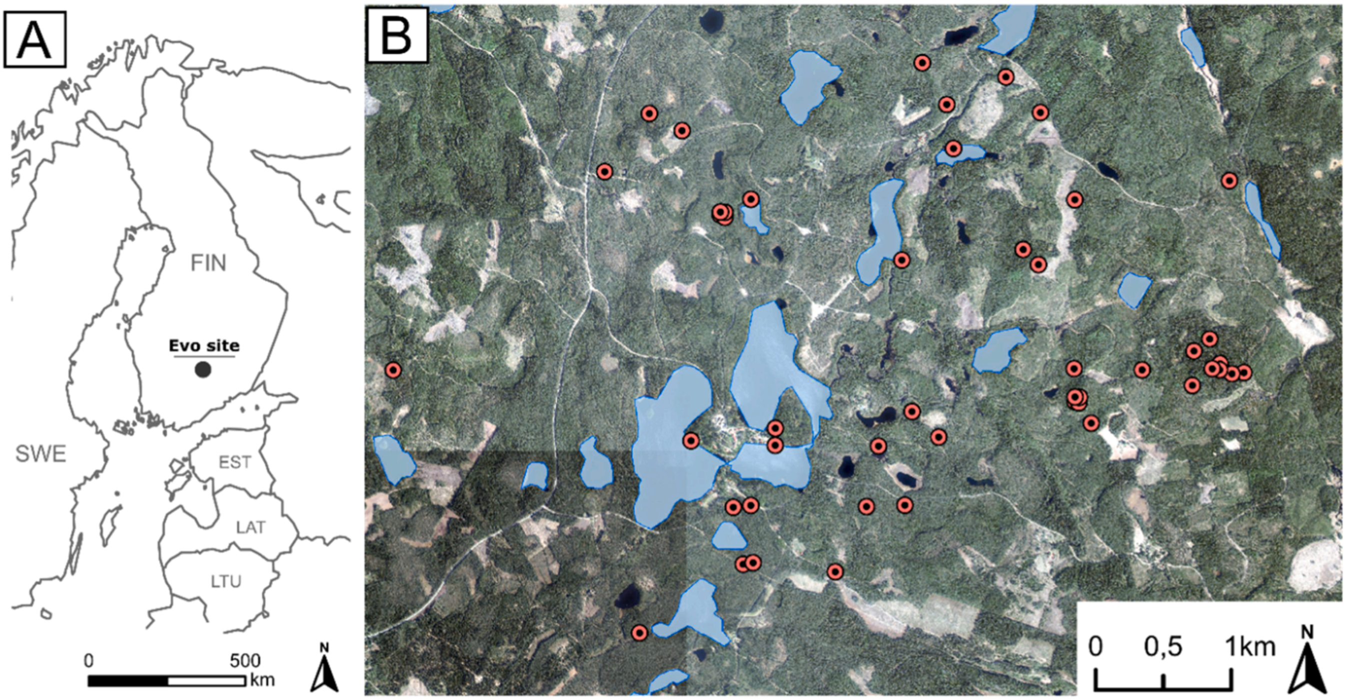

Fig. 1. **(A)** Location of the study site in Evo, Hämeenlinna, Southern Finland (61°11'48.87"N, 25°6'27.9"E). **(B)** Distribution of the 49 circular study plots in the study site.

height and densities across the area. The geographic coordinates of the plots were determined using a total station Trimble 5602 (Trimble, Westminster, United States) which was oriented to the local coordinate system using ground control points measured with a Trimble R8 Global Navigation Satellite System (GNSS) receiver, which has virtual reference station (VRS) connection capability, in open areas close to the plot. The sample plots represent diverse southern boreal forest conditions, encompassing 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.

Laser scanning point cloud data acquisition and preprocessing

This study utilizes low-, medium-, and high-density ALS data as well as TLS data, each collected at two time points—approximately at the beginning and at the end of the monitoring period—to assess forest structural complexity development over time (Fig. 2). The low-density ALS data covered years 2012 to 2019. The 2012 data was collected on May 13th using a Leica ALS50 sensor (Leica Geosystems, Balgach, Switzerland). The data was acquired from a scanning altitude of 2,200 meters, resulting in a point cloud density of 0.4 pts/m^2. The 2019 data

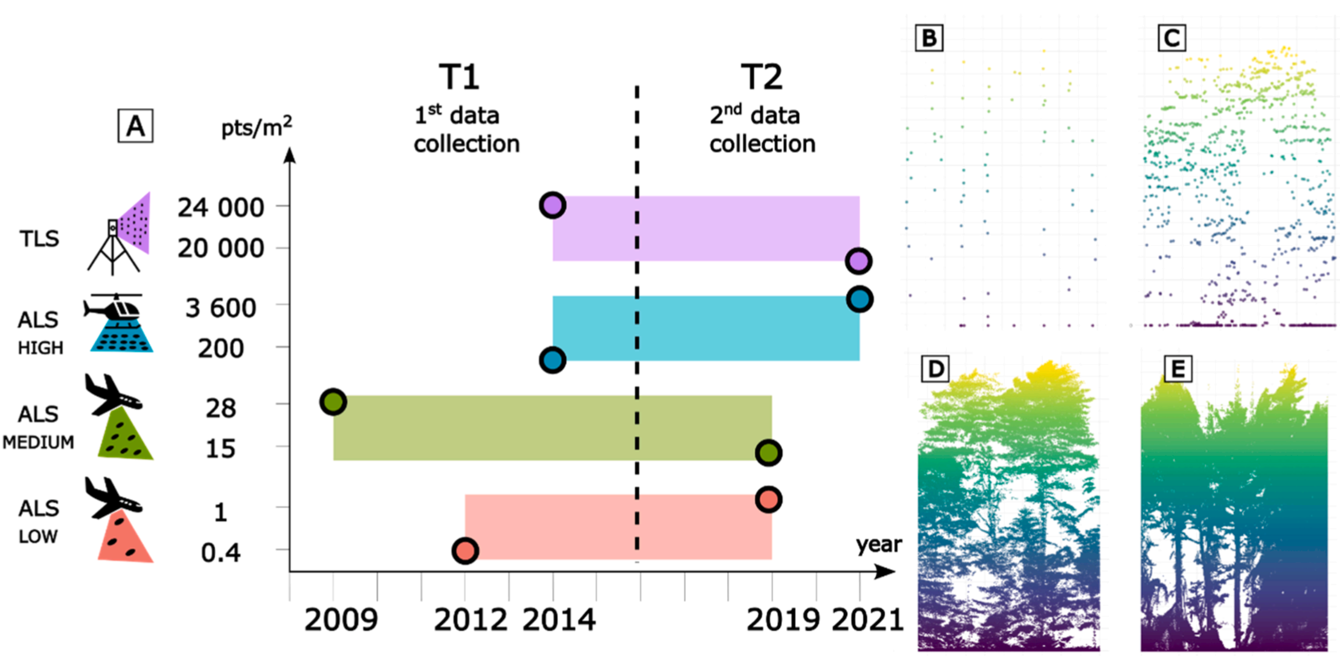

Fig. 2. (A) Summary of point cloud density and monitoring periods across sensors. (B–E) Forest vegetation visualizations using a 5-m wide transect with different point cloud densities: (B) low, (C) medium, (D) high ALS, and (E) TLS. Locations are random and do not represent the same trees.

was collected on May 6th using a Riegl VQ-1560i (Riegl Laser Measurement Systems, Horn, Austria) laser scanner at an altitude of 1755 m, resulting in a point density of 15 pts/m^2. However, the data was thinned to 1 pts/m^2 using the TerraScan software (Terra Solid, Helsinki, Finland), which evenly spaced out the points by selecting first return echoes and later return echoes corresponding to the original input pulses (National Land Survey of Finland, 2014). Both data sets featured similar quality characteristics - distance between points on the ground was approximately 1.4 m with a standard error of 15 cm for elevation and approximately 60 cm in the planar direction.

The medium-density ALS data covered years 2009 to 2019. The 2009 data was collected on July 25th using the Leica ALS50-II SN058 sensor. Data was collected from altitude of 400 m, resulting in a point density of 28 pts/m^2. The 2019 data was from the same acquisition as the low-density ALS dataset in 2019, but this dataset retained the original 15 pts/m^2 point density without any data sparsening applied.

The high-density ALS data covered years 2014 to 2021. The 2014 data was acquired in December 2014 from a helicopter using a Riegl VQ-480-U scanner at a 75 m flight altitude. The scanner operated at flight speed of 50 km/h, the data produced point clouds with a density of approximately 200 pts/m^2. The 2021 data was collected on June 22nd. Sample plots were scanned from altitude of 80 m above ground level and 50 km/h flight speed. The scanning system consisted of three Riegl scanners: VUX-1HA, MiniVUX-3UAV, and VQ-840-G. Point cloud density reached an overall point cloud density of approximately 3 600 pts/m^2.

The TLS data covered years 2014 to 2021. The 2014 data was collected in May by two field crews, one was using a Leica HDS6100 and the other a Faro Focus 3D scanner. Both scanners were utilizing a phase-shift technique with an angular resolution of 0.018°. At a 10 m distance, the point spacing was 6.3 mm. A multi-scan approach combined five scans per plot: one at the center and four auxiliary scans positioned approximately 11 meters away from the plot center at directions 45°, 135°, 225°, and 315°. The 2021 TLS data acquisition campaign lasted from late April to late May. A Leica RTC360 3D time-of-flight scanner was used producing a point cloud an angular resolution of 0.018°, resulting in a point spacing of 3 mm at a 10-m distance. Each sample plot was scanned from multiple locations: one scan from the plot center and eight auxiliary scans from positions distributed around the plot. All the scans from each of the sample plots were co-registered and merged using a Leica Cyclone Register360 software with the help of artificial reference targets (spheres with radius 198 mm) distributed around the plot, approximately five to six per sample plot. TLS point clouds from both acquisitions were thinned to a three-centimeter point spacing using the lasthin tool in LAStools software (rapidlasso GmbH, Gilching, Germany), resulting in an approximate point density of 24,000 pts/m^2 for the first and 20 000 pts/m^2 for the second data acquisition. Point cloud density reduction improved computational speed and enhanced storage management while maintaining the essential spatial information for accurate analysis.

All datasets were clipped according to borders of the 15-meter radius circular plots, and height normalization was performed by removing topography from the point clouds using the lasground tool in LAStools. After normalization, Canopy Height Models (CHMs) were generated for each dataset, with the resolution determined based on point density (Table 1). We first performed individual tree detection (ITD) using a local maximum filter (lmf) approach, following methodology presented by Popescu and Wynne (2004). Individual tree detection window size varied depending on the characteristics of each point cloud (Table 1). Next, we segmented individual trees using the method described by (Dalponte and Coomes, 2016) where the CHM-identified tree locations served as seed points for the tree segmentation algorithm. To ensure accuracy and avoid systematic over- or underestimations, we conducted a visual sensitivity analysis to optimize CHM resolution, smoothing techniques, and the parameters for both tree detection and segmentation method as summarized in Table 1.

Methods to assess structural complexity using TLS and ALS point clouds

We used eight different metrics to assess forest structural complexity at the beginning (T1) and end of the monitoring period (T2) captured by each laser scanning datasets. The mean metric values obtained at T2 were subtracted from the respective values obtained at T1 to evaluate structural complexity development over time across the sample plots. The investigated metrics included various analysis methods, each designed to quantify structural complexity of a forest stand by capturing different structural properties (Table 2). Among the employed metrics, there were ones based on grid-level analysis of either a canopy height model (CHM) or voxels, and those based on intra-plot analysis of individual tree characteristics, both of which have noticed as feasible approaches for structural complexity assessment (van Leeuwen and Nieuwenhuis, 2010).

To estimate forests canopy surface complexity, we calculated plot mean CHM. When measured at consecutive time points, plot mean CHM allows to assess canopy height increment over monitoring period. Since this metric is relatively straightforward and involves point cloud generalization into a rasterized representation, we expect to observe mean canopy height increment regardless of the laser scanning technique used. A higher mean CHM value indicates a taller canopy, enhancing the potential for greater vertical heterogeneity. The consistency of this metric development when derived using different laser scanning techniques further justifies more advanced investigations to be conducted with meaningful insights.

Forest canopy height variability over time was estimated by calculating canopy rugosity, reflecting vertical complexity of a forest stand. It was calculated as mean standard deviation of CHM values within a 3 × 3 moving window. In addition to this raster-based approach, we assessed vertical complexity through individual tree crown height variation. Tree heights were obtained as the highest laser scanning point return within each crown segment, and the Gini index (Eq. 1) was used to measure their variability within each sample plot. Similarly, we assessed individual tree crown area variation using the crown segment area as tree crown area and the Gini index to measure horizontal variability within each sample plot.

Table 1
Parameters used for canopy height model (CHM) generation, individual tree detection, and segmentation across datasets obtained using different laser scanning technologies. p2r – point-to-raster algorithm; lmf – local maximum filtering; ALS – airborne laser scanning; TLS – terrestrial laser scanning.

Canopy height model (CHM)				Individual Tree Detection		Individual Tree Segmentation
Dataset	Algorithm	Resolution (m)	Smoothing	Algorithm type	Window Size	CHM and tree location-based algorithm (Dalponte and Coomes, 2016)
Low-density ALS	pitfree (0.1m) (Khosravipour et al., 2014)	2	3 × 3	lmf (Popescu et al., 2002)	5 m	
Medium-density ALS	p2r (0.1 m) (Roussel et al., 2020)	1			Variable size (x – CHM pixel value)	
High-density ALS		0.5			2 + 0.1 * x	
TLS		0.5				

Table 2
Laser scanning-derived metrics describing variability in forest structures used in this study to characterize forest structural complexity development.

Mean CHM	**Description -** Measures the mean canopy height of a forest plot, derived from a rasterized representation of vegetation height, a canopy height model (CHM). **Interpretation -** A higher metric value implies a taller canopy and an enhanced probability of introducing a greater vertical heterogeneity.
Canopy rugosity	**Description -** Estimates variation in canopy surface structure by calculating the standard deviation of CHM values (Parker and Russ, 2004). **Interpretation -** A higher metric value implies greater vertical variability and canopy surface heterogeneity.
Gini Height	**Description -** Utilizes the Gini index (Eq. 1; Reich et al., 2022) to assess height variability among trees within a plot. **Interpretation -** A higher metric value implies a greater variation of individual tree height, implying higher vertical forest complexity.
Gini crown area	**Description -** Utilizes the Gini index to assess crown area variability among trees within a plot. **Interpretation -** A higher metric value implies a greater variation of individual tree canopy area, implying higher horizontal forest complexity.
Mean Box-dimension	**Description -** Assesses the forest stand complexity as the mean complexity of individual tree architectures within a plot, evaluated using fractal analysis Box-dimensions (Neudam et al., 2023). **Interpretation -** A higher metric value implies more complex individual tree architectures and thus a more complex stand.
Filled voxel proportion	**Description -** Partitions the sample plot into voxels and measures the proportion of vegetation-occupied space within a plot. **Interpretation -** A higher metric value implies more effective use of available resources, reflecting a more complex forest structure.
Gap fraction	**Description -** Calculates the proportion of LiDAR returns bellow 2-meter threshold to quantify canopy gap occurrence. **Interpretation -** A higher metric value indicates a greater number of canopy gaps, allowing more laser returns to be reflected from the ground or lower vegetation.
Shannon entropy	**Description -** Measures the point cloud distribution evenness across forest vertical profile. **Interpretation -** A higher metric value indicates a more uniform distribution of point cloud returns across forest vertical profile, representing structurally complex and multilayered forest (Adnan et al., 2021).

$$\textit{Gini index} = \frac{\sum_{j=1}^{n}(2j-n-1)h_j}{\sum_{j=1}^{n} h_j(n-1)} * n \tag{1}$$

where:

n = number of trees per study plot
h_j = height/crown area of the $_j$th tree
j = the rank of a tree in ascending order from 1, …, n based on the height

To account for both vertical and horizontal dimensions in structural complexity assessment, we conducted fractal analysis (box-dimension) for each tree in the study plot and computed plot-level averages to assess mean architectural complexity within a sample plot. The box-dimension of a tree was calculated by determining the number of cubic boxes required to enclose all the vegetation points in the point cloud and observing how this number varies as the size of the boxes changes (Seidel, 2018). The box-dimension of a tree or forest is represented by the slope of the straight line fitted to a plot of log(N) versus log(1/r). In this context, log() refers to the natural logarithm, N is the number of boxes of size r (with r being the edge length relative to the initial box size) required to enclose all the points of the tree or forest. Theoretical box-dimension values ranging from 1 to 3 (Saarinen et al., 2021; Seidel, 2018).

To execute more comprehensive evaluation across laser scanning techniques and analysis methods, we also tested structural complexity metrics that were not affected by tree segmentation but rather based on analysis of point cloud distribution and occupancy patterns throughout the forest stand. Gap fraction (penetration ratio) measured the proportion of gaps in the canopy, thus quantifying horizontal complexity. It was calculated as the ratio of ground points (points below a 2 m height threshold) to the total number of points. Shannon entropy was used as a vertical complexity metric to quantify vertical point cloud distribution evenness throughout a forest stand. The point cloud was divided into ten equal-sized layers with layer thickness depending on the plot's maximum height. Then we calculated Shannon entropy for each plot using Eq. 2:

$$H = \sum_{i=1}^{L} p_i \log_2(p_i + \in) \tag{2}$$

where:

H = Shannon entropy value
L = number of height layers
p_i = probability of LiDAR points in layer *i,* calculated as:

$$p_i = \frac{f_i}{N}$$

f_i is the number of points in the height layer and N is the total number of LiDAR points.
$\in$ is an infinitesimally small constant (e.g., 10^{-12}) added to prevent undefined logarithm calculations when $p_i = 0$.

Volumetric complexity of the plot was assessed through filled voxel proportions, representing how much of the available space the vegetation occupied. This metric reflects light penetration, space utilization, and resource availability within a forest stand (Juchheim et al., 2017). Filled voxel proportion was quantified as the proportion of various-sized volumetric units, voxel cubes, that were occupied by at least one laser return, to the overall number of voxel cubes within the plot. The voxel size depended on the point cloud density and matched the CHM resolution (Table 1) for each dataset: 2 meters for low-density ALS, 1 meter for medium-density ALS, and 0.5 meters for both high-density ALS and TLS datasets.

Evaluating consistency of structural complexity development derived using different laser scanning techniques and analysis methods

To determine whether different laser scanning techniques and analysis methods provided consistent observations of forest structural complexity development, we tested whether:

1) the applied metrics implied statistically significant increases or decreases during the monitoring period,
2) the direction and the magnitude of the observed change was similar with each metric-sensor combination, and
3) the observations derived using different metric-sensor combinations were ecologically plausible.

To consider two laser scanning approaches provide consistent observations with a given metric, it was assumed that both techniques recorded a similar change direction (i.e., statistically significantly increasing or decreasing from T1 to T2) as well as a similar change magnitude (i.e., no statistically different magnitudes between the techniques). To accomplish this comparison, we first conducted a paired-sample *t*-test (or Wilcoxon test for non-normally distributed data) between T1 and T2 observations for each metric and laser scanning technique. The associated p-value < 0.05 was interpreted as evidence of statistically significant change in the investigated metric. Next, we computed changes in metrics by subtracting the T1 metric values from respective T2 values and evaluated whether the directions of the observed changes were similar across the analysis methods and laser scanning techniques (i.e., introduced either increase or decrease in the metric values). Then, we assessed whether the respective metric difference magnitudes between T1 and T2 were similar by conducting paired-sample Wilcoxon tests between the metric-sensor combinations. A p-value > 0.05 was assumed to indicate a statistically insignificant difference between the magnitudes, thus implying the structural complexity development trends being similarly captured. Finally, we investigated whether the observations derived using different metric-sensor combinations implied development towards either greater structural heterogeneity or homogeneity, to verify their ecological plausibility.

To allow meaningful comparison of structural complexity assessment between laser scanning techniques and analysis methods, the experiments were conducted in two parts. In the first part, we focused on assessing the consistency of structural complexity development observations when applying different analysis methods for each laser scanning data at a time. This enabled evaluating how the chosen analysis method affected observations of structural complexity development (i.e., change significance, development direction, ecological plausibility) when applied to the same data. In the second part, the comparison was focused on assessing consistency of observations when applying the same analysis method across the different laser scanning techniques. This enabled evaluating how the chosen laser scanning technique affected the observations of structural complexity development (i.e., the change significance, development direction, and magnitude) when structural complexity was analysed using the same methodology. Altogether, these experiments aimed at providing insights into the applicability of each analysis method across laser scanning techniques and sensitivity to data properties.

Results

Consistency of capturing structural complexity development using different analysis methods

When using low-density ALS, statistically significant ($p < 0.05$) changes in forest structural complexity were observed with mean CHM, Gini height, Gini crown area, mean box-dimension, filled voxel proportion, gap fraction, and Shannon entropy (Figs. 3,4). These metrics showed stand development towards greater heterogeneity except gap fraction, Gini height and Gini crown area that showed the opposite development. However, the mean box-dimension values remained below the theoretical tree-level threshold of 1, likely indicating insufficient capability of capturing structural complexity using box dimensions with low-density ALS data. With medium-density ALS, significant changes in forest structural complexity were recorded when using mean CHM, Gini height, mean box-dimension, filled voxel proportion, gap fraction, and Shannon entropy as the measures of complexity. Of these metrics, mean CHM and Shannon entropy showed development towards greater heterogeneity while the other metrics showed development towards greater homogeneity. Similar to low-density ALS, the box-dimension values for medium-density ALS remained below its theoretical minimum, suggesting data incompatibility for such analysis method. High-density ALS captured significant changes in forest structural complexity with all metrics except Gini height and Gini crown area. Positive trends in mean CHM, mean box-dimension, filled voxel proportion, and Shannon entropy showed development towards greater heterogeneity, while a decreasing trend in canopy rugosity and gap fraction showed the opposite direction. The increase in mean box-dimension from a below-threshold value of 0.824 to a justified 1.248 was likely to be attributed to increased point density from T1 (200 pts/m^2) to T2 (3600 pts/m^2), suggesting T1 point density still insufficient for box-dimension analysis. With TLS, similar findings of metrics behaviour were compared to high-density ALS, with the exceptions that canopy rugosity showed an increasing instead of a decreasing trend, thus implying development towards greater heterogeneity instead of homogeneity, whereas filled voxel proportion did not show significant changes between T1 and T2 (Figures 3-4). TLS also consistently provided reliable box-dimension estimations at both T1 and T2, showing an increasing trend over the monitoring period.

Consistency of capturing structural complexity development using different laser scanning techniques

Mean CHM, gap fraction, and Shannon entropy showed similar, statistically significant development trends for forest structural complexity regardless of the applied laser scanning technique (Figs. 3,4). With gap fraction and Shannon entropy, similar development magnitude was also captured across data types. High-density ALS and TLS showed similar development trends also with mean CHM and mean box-dimension although with differing magnitudes. Medium-density ALS showed a statistically significant ($p < 0.05$) decreasing trend for filled voxel proportion, while low- and high-density ALS showed increasing trends, and TLS showed no statistically significant change over the monitoring period. Low-density ALS-based observations aligned with those derived using high-density ALS and TLS when mean box-dimension was used as the measure of structural complexity. However, lower-density data and high-density ALS at T1 yielded mean box-dimension values below the metric's theoretical minimum, questioning its capacity of capturing structural complexity development across laser scanning techniques.

Discussion

This study aimed to evaluate the consistency of forest structural complexity trends derived over a 7-10-year period in Southern boreal forests captured using TLS and three different ALS datasets capable of reconstructing different levels of structural details varying from low (0.4-1 pts/m^2) via medium (15-28 pts/m^2) to high (200-3600 pts/m^2) point density. We examined whether different laser scanning techniques and analysis methods produce consistent observations of forest structural complexity development in terms of the significance, the direction, and the magnitude of change in the employed metrics. The analysis methods included eight different metrics aiming to capture forest structural complexity development either from a broader-scale canopy surface-based analysis or from a finer-scale characterization of individual tree architectures. The experiment revealed the gap fraction and Shannon entropy metrics being capable of providing consistent observations of structural complexity development regardless of the laser scanning technique used. The results also showed that different laser scanning techniques could yield similar observations of structural complexity development if an appropriate analysis method was selected. In general, being able to determine true development trajectories for forest stands is challenging due to possible data-related inconsistencies likely affecting observations. Nevertheless, these findings suggest that, when carefully considering which analysis methods and laser scanning data to use, it could be possible to monitor forest structural complexity over forest stands and landscapes by having different data acquired from different parts of the inventory area. With metric values closely aligning, as those based on Shannon entropy, it might be also possible to use slightly different data collected at T1 and T2 for consistent observations and flexible monitoring strategies. If data for T1 already exists, the findings obtained in this study can also support deciding upon suitable data acquisition technique for T2 or analysis methods to use for consistent structural complexity monitoring.

The experimental setup used in this study allowed investigating how the chosen laser scanning technique affected the observations when

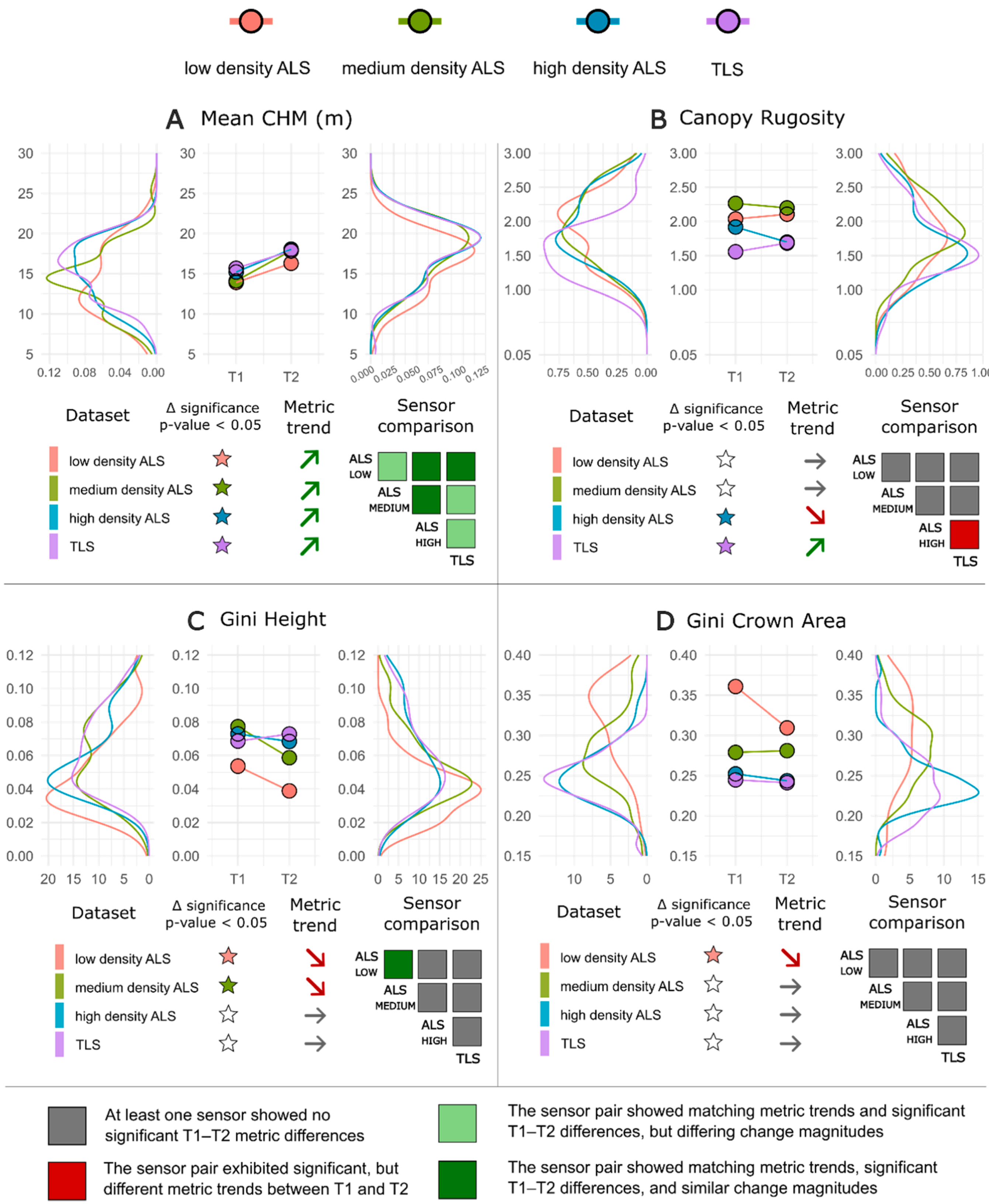

Fig. 3. A-D. Summary of changes in structural complexity metrics between two data acquisitions (T1 and T2) across 49 sample plots when derived using four different laser scanning techniques: low-density, medium-density, and high-density airborne laser scanning (ALS) and terrestrial laser scanning (TLS). The line graphs show the distribution of each metric for all 49 plots, while the middle section highlights how metric mean values changed over time for each sensor. Below each graph, the arrows indicate the direction of the change, the star colouring indicates whether the differences between T1 and T2 observations were statistically significant, and coloured boxes indicate which sensor pairs provided consistent metric dynamics with similar change magnitudes.

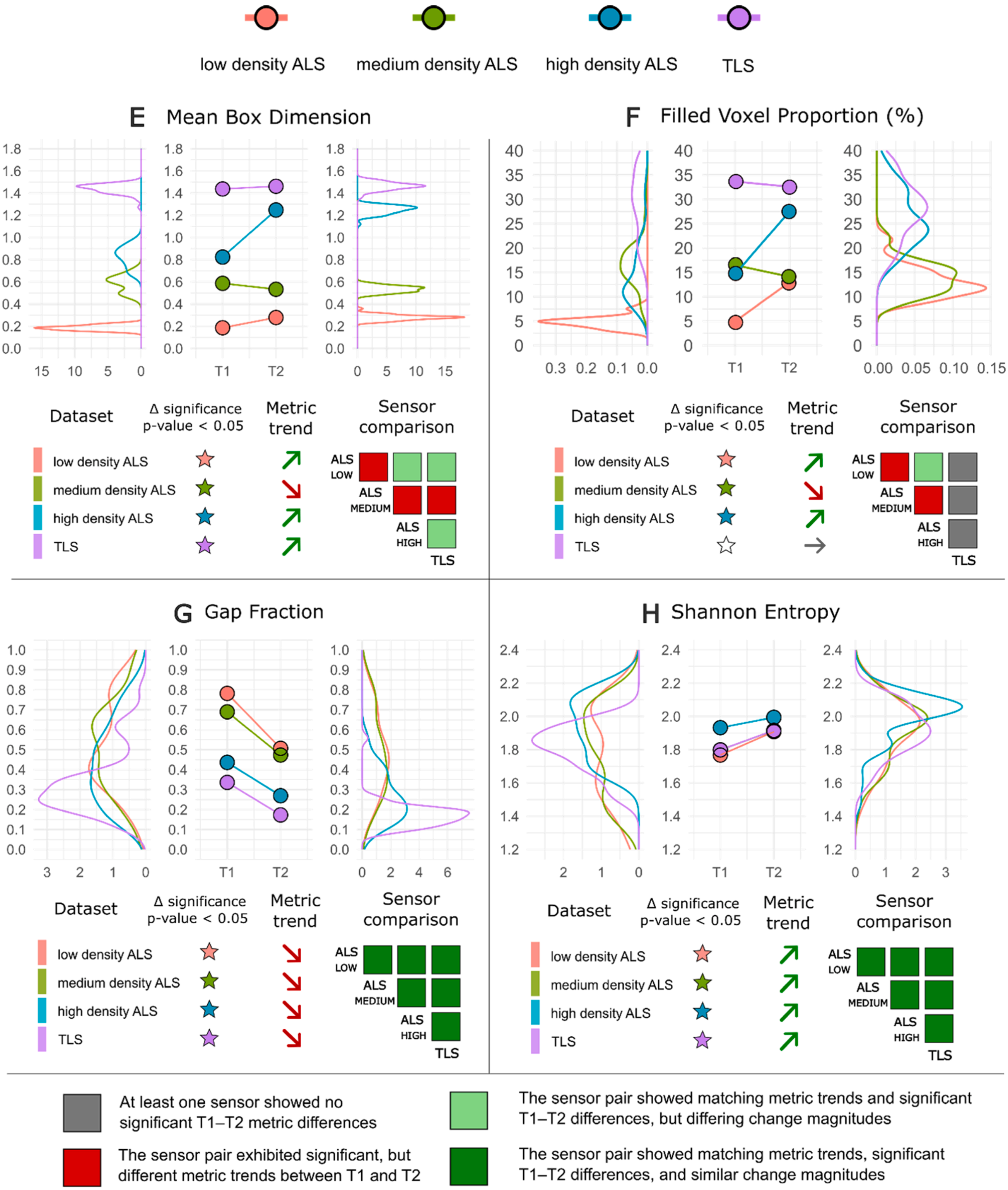

Fig. 4. E-H. Summary of changes in structural complexity metrics between two data acquisitions (T1 and T2) across 49 sample plots when derived using four different laser scanning techniques: low-density, medium-density, and high-density airborne laser scanning (ALS) and terrestrial laser scanning (TLS). The line graphs show the distribution of each metric for all 49 plots, while the middle section highlights how metric mean values changed over time for each sensor. Below each graph, the arrows indicate the direction of the change, the star colouring indicates whether the differences between T1 and T2 observations were statistically significant, and coloured boxes indicate which sensor pairs provided consistent metric dynamics with similar change magnitudes.

structural complexity development was analysed using the same analysis methods, and on the other hand, how the chosen analysis method affected the observations when using different laser scanning techniques for data acquisition. Of the investigated analysis methods, CHM-based metrics should provide more harmonized observations across different laser scanning methods as the data is first rasterized, levelling unevenness in point densities. All laser scanning methods recorded a mean CHM increment over time, implying taller canopies with enhanced probabilities of introducing greater vertical heterogeneity (Matsuo et al., 2022). The assessment of CHM variability using canopy rugosity indicated that low- and medium-density ALS data reported insignificant differences over time. In contrast, high-density ALS and TLS data showed inconsistent development trends: high-density ALS indicated a decreasing trend in canopy rugosity, while TLS showed an increasing trend. This discrepancy likely stems from the coarse CHM resolution used for low- and medium-density ALS data (2 m and 1 m, respectively), which may oversimplify canopy structure and reduce the detectable magnitude of variation, potentially obscuring actual developmental trends (Maltamo et al., 2006). High-density ALS showed a decrease in canopy rugosity over time, indicating a shift toward greater vertical homogeneity in forest structure (Parker and Russ, 2004) and lower gross primary productivity (Toda et al., 2023). On the other hand, TLS showed an increasing trend in canopy rugosity, though its under-canopy scanning geometry introduces occlusion, limiting the ability to fully characterize the upper canopy surface, which is the primary focus of this metric.

Similar to canopy rugosity, Gini tree height characterized vertical variability but through the heights of individual trees or tree groups whose crown boundaries were discerned by CHM segmentation. With this metric, no statistically significant changes in structural complexity were derived using high-density ALS and TLS. However, low- and medium-density ALS indicated decreased Gini height with similar change magnitudes, suggesting an opposite development direction for structural complexity than with mean CHM. However, these may have been influenced by the limited capacity of individual tree segmentation when based on lower-density rather than higher-density laser scanning data. Lower-density datasets are more likely to capture vegetation clusters rather than distinct trees, leading to discrepancies compared to high-density ALS and TLS (Kaartinen et al., 2012). In line with these findings, Gini crown area metrics showed no statistically significant changes across the laser scanning techniques, except low-density ALS, which most likely reflects the same reasons as pointed out already with Gini height. This aligns with expectations, as mature boreal forests without silvicultural interventions are unlikely to exhibit significant variations in tree height or crown area over the investigated 7–10-year period (Bianchi et al., 2020).

Gap fraction showed a statistically significant decrease over time, with a consistent rate of decline across all the laser scanning techniques. Denser datasets consistently introduced smaller estimates for gap fractions than sparser datasets. The observed reductions in gap fraction indicated a denser forest canopy with fewer openings and a more uniform cover throughout the sample plots, demonstrating stand development towards later successional stages (de Römer et al., 2007). The decline in canopy gaps reduces opportunities for niche species establishment, promoting development towards structural homogeneity (Vepakomma et al., 2012). Gap fraction dynamics are closely linked to canopy rugosity, and the simultaneous decrease in both metrics as obtained with high-density ALS suggests that the forest is maturing and stabilizing, with a more closed and uniform canopy surface. The increased canopy density decreases light availability in the understory, influencing species diversity and regeneration processes (Feldmann et al., 2018; Krüger et al., 2024).

Shannon entropy indicates evenness in the vertical distribution of point clouds throughout the forest profile (Adnan et al., 2021). It showed a statistically significant increase over time, with similar change magnitudes across all the laser scanning techniques, suggesting development towards more complex vegetation occupancy patterns (Liu et al., 2022). Like gap fraction, Shannon entropy is not dependent on parameter selection in CHM generation or tree segmentation. Instead, both are derived directly from point cloud data, making them robust indicators of structural complexity. These results confirm that both gap fraction and Shannon entropy effectively capture structural changes in the forest canopy, regardless of point cloud density or laser scanning geometry. However, as a vertical complexity metric, Shannon entropy showed complexity development direction that contradicted those observed with gap fraction that measures horizontal stand variability. This suggests that structural complexity can evolve at different rates in horizontal and vertical dimensions. In other words, a forest stand may appear developing towards greater homogeneous in terms of horizontal variability while simultaneously developing towards greater vertical layering. These differences might vary across different forest types, management regimes and stand development stages (Matsuo et al., 2022). Sverdrup-Thygeson et al. (2016) found that horizontal complexity metrics might be more effective than vertical metrics in distinguishing between managed and old-growth forests in Norway. This highlights the importance of considering structural complexity in multiple dimensions for a comprehensive assessment of forest structural changes (Franklin Jerry F. and Van Pelt Robert, 2004).

To consider both vertical and horizontal dimensions in assessing structural complexity development, we used metrics that described three-dimensional, or volumetric complexity. One of such metrics was mean box-dimension characterizing mean architectural complexity among trees within the sample plot. Box-dimension is recognized as point cloud-intensive volumetric structural complexity assessment, that requires detailed individual tree segmentation and precise vegetation characterization and may thus not be a suitable metric when using the lowest density point clouds. While the metric can be computed for any point cloud segment, by definition—and in the context of using it as a measure of architectural complexity of individual trees—a theoretical range for metric values is between 1 and 3 (Seidel, 2018). In practice, Saarinen et al. (2021) reported a mean box-dimension of 1.4 for Scots pines in unthinned stands in southern boreal forests. Seidel (2018) found that box-dimension values for Norway spruce in their experiment in Germany did not exceed 1.9, with consistently higher values observed in forest gaps and mixed forest conditions. In our study TLS reached an average box-dimension value of 1.44 at T1 and 1.46 at T2, but high-density ALS reached 0.82 at T1 and 1.2 at T2. Medium- and low-density ALS values remained below one, indicating that ALS-based methods, particularly at lower densities, are not well-suited for box-dimension analysis. Their limited ability to accurately segment individual trees and capture fine-scale vegetation structures below the dominant canopy layer, such as the stem and branching arrangement, reduces their compatibility for this analysis method. Even high-density ALS at T1 with 200 pts/m^2 resulted in an oversimplified tree reconstruction at T1, with mean box-dimension values below one. These findings suggest that reliable box-dimension estimations require point cloud density closer to that of T2 data which resulted in theoretically accepted mean box-dimension values with 3600 pts/m^2. In general, box-dimension is known to positively correlate with tree growth (Saarinen et al., 2021), meaning trees tend to exhibit more structural and architectural details over time. However, this does not exclude broader stand-scale complexity from developing toward homogeneity, as larger trees with advanced architecture can still be structurally similar to each other, forming monotonous stand patterns, especially in intensively managed forests or plantations (Ehbrecht et al., 2017).

As an alternative for individual tree-based volumetric assessment of stand structural complexity development, we used the filled voxel proportion as a metric to characterize vegetation occupancy directly at the stand level. Theoretically achieving a higher proportion of filled voxels with laser scanning returns requires an even distribution of returns throughout the forest profile rather than their concentration at the dominant canopy level. More evenly distributed voxel patterns suggest more multilayered and dense vegetation structure (Racine et al., 2021).

However, the development trends captured with this metric varied across the laser scanning techniques. Notably, the two highest-resolution datasets, TLS and high-density ALS, showed inconsistent development directions. TLS did not record statistically significant differences in the proportion of filled voxels, whereas high-density ALS showed a decrease in this proportion, indicating a trend toward a less dense and more simplified single-layer forest structure. Despite both techniques having the capacity to capture rather small details in the forest structure, the discrepancy here might be explained by their different data acquisition geometries that are likely to result in reconstructing the vegetative structures differently, especially with multi-layered stands. Meanwhile, both low- and high-density ALS showed an increase, with a noticeable rise at T2. This is likely due to their sensitivity to point cloud density, as both experienced the largest increase between T1 and T2 (low-density ALS from 0.4 to 1 pts/m^2 and high-density ALS from 200 to 3600 pts/m^2). These findings raise a concern that the sharp increase in metric values from T1 to T2 is more likely driven by increased point cloud density rather than actual structural changes in the forest structure, suggesting metric sensitivity to laser scanning data properties and thus possible incompatibility for cross-use between different laser scanning techniques.

Based on the findings obtained in this study from comparison between different laser scanning techniques and analysis methods for assessing structural complexity development, it should be noted that the absolute metric values changed between data types, confirming that it would not be feasible to use different data types for obtaining T1 and T2 observations directly. Instead, if the same analysis method is used and the obtained development directions and magnitudes are matching, it should be theoretically possible to use different data types collected across the inventory area without sacrificing the ability to discern stands that are developing towards greater heterogeneity or homogeneity. Metric calibration on sample plots could enable using different data at different time points as well, although it was not explicitly tested in this experiment. However, if the objective is instead to distinguish stands that feature a higher degree of structural complexity than the others, then one time-point data from different sensor-platform combinations could be rather sufficient.

Methodological aspects potentially affecting cross-comparison in the structural complexity development monitoring capacity between laser scanning techniques include the point cloud acquisition configuration along with the size of the sample plot. With ALS, factors such as scanning angle, sensor characteristics, terrain properties, and scanning distance influence the actual laser footprint size, affecting vegetation reconstruction (Hirata, 2004; Roussel et al., 2017). Additionally, the Gini height and Gini area among other laser scanning-based metrics can be sensitive to plot size and the applied CHM resolution potentially impacting the comparability of different laser scanning methods (Adnan et al., 2017). Low- and medium-density ALS data have a limited ability to capture lower vegetation layers as effectively as the high-density ALS and TLS due to the lower density of point returns to reconstruct the stand structure in general and understory vegetation in particular (Campbell et al., 2018). It should be also noted that, in this study, the low-density ALS data at T2 was derived by thinning the original, higher-density dataset, potentially altering vegetation representation and point distribution properties (Lyu et al., 2024), compared to an initially low-density ALS data. For accurate temporal comparisons, phenological alignment of the data acquisition campaigns and consistent point cloud densities between T1 and T2 can be considered essential. For example, one dataset captured within leaf-off and the other within leaf-on conditions might have an influence on the observed change in the applied metrics. In our study, the high-density ALS presented such phenological misalignment between the data acquisitions, as the T1 data was collected in leaf-off conditions in December while the T2 data was captured in leaf-on conditions in June. Alongside the significant increase in point density from T1 to T2, this might have had an influence on observations that were contradicting with those derived using TLS (filled voxel proportion) as well as the sharp increase in mean box-dimensions. The influence is likely to be most prominent for deciduous-dominated sample plots, although the study site mostly featured conifers-dominated stands. With TLS, the T2 campaign was conducted using a significantly enhanced scan setup, in terms of scanner resolution and the scan coverage across the sample plots. However, this influence on the utilized analysis methods was mitigated by concentrating on 15-m radius circular sample plots that were covered sufficiently using both campaigns, while differences in point densities were unified through 3-cm downsampling. It is also worth mentioning that TLS data was mostly acquired during leaf-off conditions, representing a phenological offset with T2 high-density data. However, point cloud acquisition geometries between the two techniques is likely to have a more significant effect on their capacities of capturing structural complexity development even for deciduous-dominated stands.

Characterizing forest structural complexity is not as straightforward as, for example, estimating typical forest inventory attributes that characterize the total stem volume or biomass of the woody parts of standing trees, as it is challenging to be quantified with a single metric and standardized units across different forest conditions. In this study, we used eight different analysis methods that aim to characterize the structural complexity of a boreal forest stand slightly differently. For example, metrics such as mean CHM, Gini Height, canopy rugosity, and Shannon entropy evaluate vertical complexity, while gap fraction and Gini crown area describe horizontal complexity. Filled voxel proportion and mean box dimension then aim to capture both dimensions with a more volumetric approach. Due to these differences, inconsistencies between different metrics can occur. In some conditions, it can be possible that the vertical complexity seems to decrease while horizontal complexity seems to increase, showing contradicting signs of overall complexity development. While analysis methods characterizing volumetric complexity aim to solve this challenge, our findings showed the lowest consistency between laser scanning approaches with mean box-dimensions and filled voxel proportion. A continuation of this study could explore machine learning approaches to align structural complexity metrics across different laser scanning platforms by identifying consistent patterns in multi-sensor data. Additionally, future research could investigate how forest type, age, and management history influence metric behavior and stability. Understanding these factors can help tailor metric selection to specific forest conditions and monitoring objectives. Altogether, our study highlights the strengths and limitations of different laser scanning-based methods for assessing forest structural complexity. Choosing which analysis method to use and how to interpret the observations should thus be adjusted based on the aim of the monitoring campaign and laser scanning data characteristics.

Conclusion

Advances in laser scanning technologies have brought alternative data acquisition techniques for forest characterization. To ensure reliable monitoring of forest structural complexity, it is essential to identify analysis methods that remain consistent across different laser scanning techniques introducing variability in point densities and data collection geometries. As sensor technology advances, it will become more common that the inventory area is covered with different laser scanning techniques, representing different data modalities and capacities in capturing structural complexity. This requires careful metric selection to maintain consistency of observations derived with different data types to improve forest monitoring accuracy over extended timeframes. This study evaluated forest structural complexity development using various laser scanning techniques, revealing key differences in metric reliability and sensitivity to point cloud characteristics. Two-dimensional structural complexity metrics showed greater consistency across laser scanning techniques compared to three-dimensional metrics, aligning with previous research. Gap fraction and Shannon entropy were proved to be robust metrics, capable of consistently capturing structural development trends across investigated laser scanning techniques. In contrast, three-dimensional complexity metrics like mean box-dimension and filled voxel proportion were more sensitive to point cloud density, leading to inconsistent observations of structural complexity development across the laser scanning techniques. Gini height and Gini crown area showed no significant changes, highlighting their more limited capacities over the other metrics in detecting structural development over the relatively short 7–10-year monitoring period.

CRediT authorship contribution statement

Reinis Cimdins: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tuomas Yrttimaa:** Writing – review & editing, Validation, Supervision, Software, Methodology, Investigation, Conceptualization. **Juha Hyyppä:** Writing – review & editing, Data curation, Conceptualization. **Mikko Vastaranta:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Data curation. **Ville Kankare:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization.

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.

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Data availability statement

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

Data availability

The authors do not have permission to share data.

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