

Dissertationes Forestales 384

**Boreal forest structural complexity assessments with
laser scanning**

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Academic dissertation

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ABSTRACT

Forest structural complexity is a key indicator of ecosystem functioning, influencing biodiversity, habitat availability, and forest resilience. Yet, comprehensively capturing it remains challenging, and its temporal dynamics in boreal forests are still poorly understood. Laser scanning technologies enable detailed quantification of forest structure, but significant knowledge gaps remain regarding how different technologies capture structural complexity and its changes over time. This dissertation addresses these gaps by evaluating airborne laser scanning (ALS) and terrestrial laser scanning (TLS): (1) for assessing structural complexity in boreal forests using bi-temporal ALS data; (2) for examining how different scanning technologies and processing approaches capture structural complexity; and (3) for investigating the agreement and consistency of structural complexity metrics derived from bi-temporal point cloud datasets.

Study I assesses the feasibility of bi-temporal low-density ALS (<1 pt m^2) for monitoring changes in structural complexity under varying light conditions. Using ALS data from 2012 and 2019, canopy vertical profiles were generated by voxelizing point clouds into $4 \times 4 \times 1$ m units and classifying them into light penetration categories. Forest stands with higher structural complexity showed greater vegetation occupancy and less empty space beneath the canopy. The results demonstrate that low-density ALS can detect structural development over time.

Study II compares ALS- and TLS-derived structural complexity metrics using grid- and object-level processing across three dimensions: vertical, horizontal, and volumetric. Helicopter-borne ALS and multi-scan TLS data were analyzed at both levels. Object-level processing produced greater metric variation for both sensors, better capturing detailed spatial information. High-density ALS effectively characterized vertical and horizontal complexity at the object-level (individual trees), showing strong agreement with TLS. However, differences in measurement geometry reduced consistency in volumetric complexity estimates between sensors.

Study III examines how point cloud characteristics influence structural complexity monitoring over 7–10 years. Three ALS datasets (0.4–1, 15–28, and 200–3600 pts/ m^2) and TLS data were analyzed to evaluate metric consistency. Gap fraction and Shannon entropy showed consistent trends across datasets, while vegetation occupancy and fractal dimension were more sensitive to point cloud properties. These findings emphasize careful metric selection and indicate that robust indicators enable reliable cross-sensor, large-scale monitoring of boreal forest structural complexity.

Overall, this thesis evaluates how airborne and terrestrial laser scanning technologies capture and monitor forest structural complexity over time, identifying reliable metrics and methods for representing structural changes across varying point cloud types and densities in boreal forests.

Keywords: forest structural complexity, light detection and ranging LiDAR, canopy vertical profiles, voxel-based analysis, biodiversity, precision forestry, forest monitoring

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Stāmeriena (Latvija), March 2026.
Reinis Cimdiņš

LIST OF ORIGINAL ARTICLES

This thesis is based on the following research articles, referred to by the Roman numerals **I–III**. Articles **I–III** are reprinted with the permission of the publishers.

- I** Cimdins, R., Yrttimaa, T., Hyypä, J., Vastaranta, M. and Kankare, V., (2024) Quantifying changes in forest structural complexity using bi-temporal airborne laser scanning. *European Journal of Remote Sensing*, 57(1), p.2417905.
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- II** Cimdins, R., Yrttimaa, T., Vastaranta, M. and Kankare, V., (2025) Assessing forest structural complexity: insights from alternative laser scanning approaches. *Scandinavian Journal of Forest Research*, 1-14.
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- III** Cimdins, R., Yrttimaa, T., Vastaranta, M. and Kankare, V., (2025) Capturing trends in forest structural complexity development using various laser scanning techniques. *Trees, Forests and People*, 21, 100954.
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AUTHOR CONTRIBUTION

The articles were planned collaboratively with the supervisors. Cimdins collected terrestrial laser scanning (TLS) data for study II and III. Cimdins was responsible for the analyses, calculations, analysis development, and accuracy evaluation in all three studies. As the main author, he wrote the initial drafts of all the manuscripts and led the review processes. The final written versions of the articles were improved by the contributions of all co-authors.

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ABBREVIATIONS

ALS	Airborne Laser Scanning
ATV	All-Terrain Vehicle
CHM	Canopy Height Model
CV	Coefficient of Variation
CVP	Canopy Vertical Profile
DBH	Diameter at Breast Height
GNSS	Global Navigation Satellite System
heli-ALS	Helicopter-Borne Laser Scanning
ITD	Individual Tree Detection
LiDAR	Light Detection and Ranging
MLS	Mobile Laser Scanning
pts	Points
RADAR	Radio Detection and Ranging
SDI	Stand Density Index
T1	Time Point at the Beginning of the Monitoring Period
T2	Time Point at the End of the Monitoring Period
TLS	Terrestrial Laser Scanning
UAV-LS	Unmanned Aerial Vehicle Laser Scanning
VRS	Virtual Reference Station

1 INTRODUCTION

1.1 Forest structural complexity and its importance in boreal forest governance

The boreal forest, or taiga, is the world's largest terrestrial biome, stretching across North America, Fennoscandia, Russia, and parts of China (Saucier et al., 2015). Dominated by cold-tolerant coniferous species such as pines (*Pinus sylvestris* L.), spruces (*Picea abies* (L.) H. Karst), firs (*Pseudotsuga menziesii* (Mirb.) Franco), and larches (*Larix decidua* Mill.)—with scattered deciduous trees like birches (*Betula pendula* Roth) and aspens (*Populus tremuloides* Michx)—these forests are known for their relatively low species richness and productivity compared to tropical or temperate systems (Kayes & Mallik, 2020). Despite their relatively low species richness, boreal forests are vital for global carbon storage, climate regulation, and biodiversity conservation. These ecosystem functions are deeply intertwined with forest structural complexity describing the three-dimensional arrangement of vegetation, including variations in tree size, canopy layering, understory vegetation, and deadwood (McElhinny et al., 2005). Structural complexity can be assessed across multiple levels of biological organization and at various spatial and temporal scales (LaRue et al., 2023). This dissertation focuses on the aboveground component of forest structural complexity specifically the structure and spatial arrangement of trees, canopy architecture, and vegetation layering—using remote sensing technologies.

Forest structural complexity influences a wide range of ecosystem functions, including carbon storage, microclimate regulation, habitat provision, and nutrient cycling (Crockett et al., 2023; Murphy et al., 2022). It is also a strong predictor of net primary productivity, as it integrates key drivers of forest growth—such as canopy occupancy (Lefsky et al., 1999), crown connectivity (Davies & Asner, 2014), and light absorption efficiency (Atkins et al., 2018; Gough et al., 2019). Beyond its influence on ecosystem processes, structural complexity is fundamental to biodiversity as the three-dimensional arrangement of vegetation determines the availability of ecological niches, species distributions, and influences animal behavior and community dynamics (MacArthur & MacArthur, 1961). Across many taxa, from birds to primates, structural complexity has consistently been identified as a key factor governing species diversity, predation patterns, and opportunities for coexistence (Tews et al., 2004).

Any changes in structural complexity, whether from natural succession, disturbance, or human intervention—can significantly alter forest ecosystem functions (Ehbrecht et al., 2017). In the boreal zone, forest structural complexity is increasingly altered by extensive logging and mining, as well as by accelerating climate change, which drives rising temperatures, permafrost thaw, more frequent wildfires and windthrow events (Gauthier et al., 2015; Seidl et al., 2017), and shifts species compositions (Antão et al., 2022). Forest management plays a key role in shaping forest structure by influencing spatial patterns, species composition, and tree size distributions (Li et al., 2023). Forest management strongly shapes stand structure and composition, often resulting in more homogeneous stands through practices such as clear-cutting, even-aged management, and intensive thinning. Where intensive interventions typically reduce structural complexity, Nature management or uneven-aged silviculture practices can help retain or restore heterogeneity and more natural spatial arrangements (Schall et al., 2018).

Understanding and monitoring forest structural complexity and its dynamics has become an important task for researchers, policymakers, and land managers (Barredo et al., 2021). Global forest policy frameworks such as the Montréal Process (Payn, 2023) and Closer-to-Nature Forest Management guidelines (European Commission, 2023) have acknowledged the significance of forest structural complexity. However, monitoring forest structural complexity remains challenging due to limited data availability, differences in data compatibility, resolution, and acquisition geometry, as well as occlusion effects and high acquisition and processing costs. Further difficulties arise from substantial structural variability across biomes (de Conto et al., 2024; Ehbrecht et al., 2021; Kreft & Jetz, 2007), the subjectivity of metric selection, and the lack of direct field-based measurements for validating remote sensing–derived estimates.

1.2 Structural complexity assessments

Traditionally, ecosystems have been assessed using measures of species richness and genetic composition (Hunter, 1999). However, these biodiversity-based approaches can overlook critical ecological processes such as nutrient cycling, disturbance dynamics, and decomposition, which are essential for maintaining ecosystem health (Noss, 1990). Biodiversity metrics can also be ambiguous, vary with spatial and temporal scale, and are difficult to measure consistently due to taxonomic uncertainties and seasonal fluctuations, making them less practical for routine monitoring and management (Azaele et al., 2015; Leroy et al., 2023). To capture the physical arrangement and variability of vegetation—such as canopy layering, tree spacing, deadwood, and understory structure—early ecologist work and (Watt, 1947; Whittaker & Woodwell, 1969) described forest structure as a measurable indicator of ecosystem function. This concept has since developed into what is now known as structural complexity, which is directly observable and closely tied to habitat availability and key ecological processes (Franklin et al., 2002; McElhinny et al., 2005b). While biodiversity indicators remain valuable for assessing species composition and conservation status, structural complexity offers a complementary and often more scalable framework for monitoring ecosystem function. Structural metrics are typically less affected by seasonal variation and observer bias, making them especially useful for long-term forest assessment, management, and restoration planning (Jayathunga et al., 2018).

Forest structural complexity has traditionally been assessed using conventional field measurement tools such as tape measures, calipers, and clinometers, which provide accurate measurements of tree diameter at breast height (DBH), tree height, and canopy base height (McElhinny et al., 2005; Pretzsch, 2010). These core variables can be used to calculate the key structural indices such as stand density index (SDI), the Gini coefficient for tree height variation and canopy openness (Keren et al., 2020; Sharma, 2016). Structural complexity can also be described by identifying specific structural elements like number of large trees, standing and lying deadwood, and biodiversity indicator species (Lassauce et al., 2011; Lutz et al., 2018). While conventional methods are accurate (Luoma et al., 2017) at the plot scale and provide valuable ecological insight, they are time-consuming, labor-intensive, and impractical for large-scale or repeated assessments (Zenner & Hibbs, 2000). Additionally, certain characteristics of structural complexity—such as three-dimensional crown architecture, vertical canopy connectivity, light absorption and fine-scale vegetation layering—are difficult or impossible to capture reliably using conventional field

measurements alone. Furthermore, replicating such detailed measurements across entire landscapes or regions is often unrealistic due to logistical and financial constraints. These limitations have led researchers to increasingly use remote sensing technologies, which offer more scalable and consistent tools for assessing structural complexity at broader spatial and temporal scales (Camarretta et al., 2020).

Remote sensing is defined as the acquisition of information about Earth's surface or object without direct contact, using satellite, airborne, or ground-based sensors, offering scalable, non-destructible, repeatable, and cost-efficient data collection across large spatial and temporal scales (Lillesand et al., 2015). Over the past decades, remote sensing has rapidly gained popularity in ecological research and management, fundamentally transforming how forest scientists and ecologists monitor structural attributes (Fassnacht et al., 2024). It provides new perspectives on ecosystem structure, enabling consistent assessments from the level of individual trees to entire landscapes (Toivonen et al., 2023).

Remote sensing technologies are generally classified into two types: passive and active sensors. Passive systems, such as standard optical camera, multispectral, and hyperspectral cameras (e.g., Sentinel-2, Landsat, PRISMA), rely on sunlight and detect the natural reflectance of vegetation (Kacic & Kuenzer, 2022). These systems are widely used to monitor vegetation health, species composition, and surface characteristics due to their rich spectral information (Wang et al., 2024). Although passive satellite sensors have been employed to infer aspects of forest structure, their capacity to capture three-dimensional structural complexity is limited. These sensors primarily rely on two-dimensional spectral data, which cannot fully represent the vertical variability and spatial heterogeneity characteristic of complex forest canopies. Moreover, in dense forests, structural proxies derived from such data often become saturated (Jha et al., 2021). Passive sensors effectiveness can be limited by atmospheric conditions and persistent cloud cover—particularly in high-latitude regions like boreal forests, making them less reliable for structural assessments under certain conditions (Wulder, 1998).

In contrast, active remote sensing technologies—such as LiDAR (Light Detection and Ranging) and RADAR (Radio Detection and Ranging)—emit their own energy signals and measure the reflected returns, allowing for highly accurate and detailed three-dimensional representations of forest structure regardless of lighting or weather conditions (Campbell & Wynne, 2011). This makes active remote sensing especially valuable for assessing forest complexity related attributes like canopy layering, foliage, height diversity, crown architecture, and vertical continuity, which are difficult to capture with passive systems or with traditional field methods (Andersen et al., 2006; Maltamo et al., 2014; Vastaranta, 2012; Wulder et al., 2014). Given its robustness and precision, active remote sensing is a central focus in modern forest structural complexity research and is increasingly being integrated into restoration monitoring, biodiversity conservation, and adaptive forest management frameworks like REDD+ (Calders et al., 2020). Compared to RADAR, LiDAR is the preferred technology for forest assessments in Northern Europe due to its higher spatial resolution, greater ability to penetrate forest canopies, and capacity to capture detailed vertical and horizontal forest structure (Kangas et al., 2018; Lefsky et al., 2002). LiDAR data are generally easier and cheaper to collect, especially with airborne or drone-based systems, making it more practical for targeted, high-resolution campaigns (White et al., 2016). Additionally, LiDAR systems are more customizable for specific forestry needs and have become widely adopted in Northern European Forest inventories, research, and remote sensing applications (Maltamo et al., 2021). By collecting multiple return signals, LiDAR produces a detailed point cloud, which serves as a key data source for characterizing

vegetation layers and understory vegetation (Valbuena et al., 2020). However, the quality and level of detail in LiDAR point clouds depend on various platform and sensor related aspects –and acquisition parameters, such as, pulse repetition rate, return registration principle, scan angle, footprint size, and flight altitude and speed (Baltasvias, 1999; Dayal et al., 2020). These factors directly influence the capabilities of forest structure assessments, affecting the ability to analyze features such as fine-scale tree architecture, canopy gaps, and large-scale forest composition (Strunk et al., 2012).

LiDAR technology has become a leading tool for quantifying forest structural complexity due to its ability to generate precise, consistent, and multi-scale three-dimensional information across broad spatial extents (Atkins et al., 2018; Coops et al., 2021; LaRue et al., 2020). Since early laser altimeter applications demonstrated its value for assessing canopy light properties (Lefsky et al., 1999), LiDAR has played an increasingly important role in ecological and forest structural studies (Camarretta et al., 2020; van Leeuwen & Nieuwenhuis, 2010). By capturing detailed variation in vegetation structure, LiDAR provides insights into habitat complexity and its influence on species behavior, movement, and community dynamics (Vierling et al., 2008). This has enabled global investigations into ecological patterns, including bird foraging and detectability (Davies & Asner, 2014; Davison et al., 2023), bat and arthropod activity (Froidevaux et al., 2016; Wildermuth et al., 2024), predator–prey interactions (Lone et al., 2014), and large mammal distributions (Petersen et al., 2023). Such multiscale organism–habitat relationships benefit from LiDAR's capacity to represent canopy, understory, and terrain complexity (Goetz et al., 2007).

A wide range of LiDAR platforms (i.e. laser scanning) combining LiDAR with IMU and GNSS sensors in a stationary or moving platforms support forest structural complexity analysis, each suited to different spatial scales and research objectives. Terrestrial laser scanning (TLS) provides highly detailed, bottom-up structural information at tree and plot levels, particularly useful for capturing stem form and understory layers, though limited in spatial coverage (Liang et al., 2016; Yrttimaa et al., 2024). Mobile laser scanning (MLS)—whether handheld or vehicle-mounted—offers greater mobility in complex environments but typically with lower precision than TLS (Jaakkola, 2015). Airborne laser scanning (ALS), deployed from fixed-wing aircraft or helicopters, efficiently captures canopy structure over large areas, although with reduced detail on stems and understory vegetation (Goodbody et al., 2017). Unmanned aerial vehicle laser scanning (UAV-LS) provides a bridge between TLS/MLS and ALS by offering high-resolution, flexible, above-canopy data at stand to landscape scales (Goodbody et al., 2017). At the broadest scale, spaceborne laser scanning systems such as ICESat-2, GEDI enable global forest monitoring but have lower spatial resolution and limited control over acquisition patterns (Dhargay et al., 2022; Lefsky et al., 2005).

1.3 Quantifying structural complexity with laser scanning

To support ecological interpretation laser scanning-derived forest structural complexity is typically expressed through quantitative metrics. These range from simple metrics, such as the number of large trees, to more advanced indices, such as TLS-based understory complexity metrics (Seidel et al., 2019) and species distribution indices (Clawges et al., 2008). In ecological applications, the choice of metrics should be guided by the relevance to the research question, the spatial and temporal scale of the analysis, and the feasibility of

acquiring and processing the necessary laser scanning data. Forest structural complexity is typically described across three dimensions—vertical, horizontal, and volumetric—each capturing key ecological aspects of forest architecture (Franklin & Van Pelt, 2004; Seidel et al., 2019). Despite significant progress, no standardized procedure currently exists for consistently measuring and interpreting forest structural complexity (Reich et al., 2022).

The level of detail which forest structural complexity can be assessed depends both on the research objectives and on the density of the available point cloud data (Whelan et al., 2023). Metrics describing the spatial arrangement of vegetation can be derived directly from point clouds or calculated from voxelized or rasterized outputs such as canopy height models (CHMs), which typically provide grid-level indicators (Kukunda et al., 2019). With higher-density point clouds, more detailed analysis becomes possible (Jakubowski et al., 2013). In such cases, individual trees can be segmented from stand-level data, allowing the extraction of object-level metrics that capture fine-scale attributes such as crown shape, height, and branch architecture (Seidel & Böttger, 2023).

Vertical structural complexity

Vertical structure describes the distribution of vegetation and biomass along the vertical axis, sometimes referred as canopy layering or stratification (Parker & Brown, 2000). It reflects the presence and density of foliage, branches, and tree crowns at different heights. These characteristics are tightly linked to stand development phases. With forests maturity, vertical layering increases through processes like gap formation, shade-tolerant species regeneration, and canopy diversification (Rissanen et al., 2019). For example, in old-growth forests, foliage and live branches often form a continuous structure from the ground to the canopy, a result of species succession, and mortality processes (Shaw, 2004). Vertical structural complexity and layering play a key role in shaping habitat quality and biodiversity. It creates diverse microhabitats that support species with different ecological conditions (Oliveira & Scheffers, 2019). Complex vertical structure also buffers microclimates by stabilizing temperature and humidity, which benefits sensitive species (Starck, 2025). This progression marks ecological development and resilience, making vertical complexity a reliable indicator of forest health. Structural complexity metrics help characterize stand maturity and predict ecological variables such as species richness, habitat availability, and carbon storage (Zellweger et al., 2013). Laser scanning based metrics to assess vertical structure include point return height percentiles (Mund et al., 2015), Vertical layering indices (Jaskierniak et al., 2011), gap fraction (Sasaki et al., 2016), Shannon entropy (Kissling & Shi, 2023), tree height variation (Ozdemir & Donoghue, 2013), modelled tree height diversity indices (Mura et al., 2015), canopy height variation (Zimble et al., 2003) and rumple index (Karna et al., 2020), and point return distribution curve analysis (Valbuena et al., 2013).

Horizontal structural complexity

Horizontal forest structure describes the spatial arrangement and variability of vegetation across the forest floor and canopy in a horizontal plane. It captures how trees, gaps, and understory elements are distributed horizontally, encompassing aspects such as canopy cover, gap size and distribution, and canopy patchiness. This structure emerges and evolves through disturbances, species interactions, and stand development (Vepakomma et al., 2008). Horizontal structural complexity influences species composition by creating spatially diverse microhabitats. Horizontal structural complexity helps spatial heterogeneity and its ecological consequences, such as light availability, regeneration potential, and habitat diversity (Szmyt & Tarasiuk, 2018). Forests with varied gap sizes, dense patches, and irregular canopies

support a broader range of species, especially those dependent on gap edges and open areas (Erasmey et al., 2021). In contrast, homogenous horizontal patterns—often seen in intensively managed stands—limit niche diversity and reduce habitat quality for many organisms (Kern et al., 2014). Over time, natural disturbances such as windthrow, fire, or mortality generate spatial mosaics and promote horizontal structural heterogeneity (Girona et al., 2023). These structurally complex patterns are crucial for successional dynamics and resilience, influencing regeneration and maintaining long-term forest function (Falk et al., 2022). Metrics commonly used to quantify horizontal structure include canopy cover (Vehmas et al., 2011), continuous canopy patterns (Goodbody et al., 2020), tree canopy area variation (Jung et al., 2011), modelled tree DBH diversity indices (Mura et al., 2015), number of large trees for example aspens that are hosts and habitat for a wide range of forest-dwelling species (Toivonen et al., 2024).

Volumetric structural complexity

Volumetric structural complexity refers to the three-dimensional distribution of vegetation and characterizes how plants physically occupy space within a forest. It captures not only the vertical and horizontal arrangement of vegetation but also characterizes density, volume of foliage, branches, and stems distribution across multiple canopy layers and gaps (Seidel, 2018). Volumetric structural complexity offers holistic and unified representation of forest structure, supporting improved assessments of biomass, habitat quality, and ecosystem functioning (Seidel & Ammer, 2023). Ecologically, volumetric complexity is tightly linked to processes like photosynthesis, transpiration, and productivity (LaRue et al., 2023). Forests with higher volumetric complexity tend to have more leaf area and foliage volume, supporting greater primary production and carbon sequestration (Hardiman et al., 2013). Additionally, a higher degree of volumetric complexity provides opportunities for niche species and support diverse organisms like birds and insects to epiphytes and arboreal mammals (Rechsteiner et al., 2017). Volumetric structure also reflects the developmental history and successional stage of a forest. Early successional stands may exhibit low volumetric complexity with biomass concentrated near the ground or upper canopy, whereas mature forests typically display more uniform biomass distribution across strata (Campos et al., 2021). This progression signals structural maturity, ecological stability, and higher resilience to disturbances such as windthrow or drought. Metrics used to assess volumetric complexity often rely on fractal analysis (Seidel, 2018), voxel-based laser scanning approaches (Hess et al., 2018; Lecigne et al., 2018), leaf area density (Hosoi et al., 2013) and plant area index (Grau et al., 2017). These metrics quantify how vegetation is distributed throughout space, indicating how much “structural space” is occupied, and where gaps or voids exist within the canopy.

1.4 Thesis objectives

Boreal forests are experiencing rapid change, which is why reliable, scalable monitoring of forest structural complexity is increasingly needed. Although laser scanning offers great potential, uncertainty remains about how different platforms, point densities, and acquisition geometries affect the accuracy and consistency of structural metrics. The aim of this thesis is to assess the feasibility and reliability of laser scanning technologies for monitoring forest

structural complexity across spatial and temporal scales and to evaluate their suitability for ecological and forest management applications by addressing three main objectives:

1. Can low-density ALS reliably detect temporal changes in forest structural complexity, particularly in relation to vegetation occupancy and light penetration?
2. How do object-level and grid-level structural complexity metrics derived from ALS and TLS compare across vertical, horizontal, and volumetric dimensions?
3. How do point cloud density and scanning geometry influence the consistency and robustness of forest structural complexity metrics across different laser scanning datasets?

2 MATERIAL AND METHODS

2.1 Study area

Datasets for **Studies I, II, and III** were collected from the same research area in Evo, Southern Finland (61°11'48.87"N, 25°6'27.9"E), located within the southern boreal forest zone and dominated by Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) H. Karst.), and birch species (*Betula* spp.). The terrain is relatively flat, with an average elevation of approximately 135 m above sea level. To guide the study plot selection, we performed preliminary analysis using ALS-derived metrics (Figure 1). Specifically, canopy height and vegetation density at 2 m height were calculated for each 32 m × 32 m grid cell across the study area (Yu et al., 2015). These metrics were then used to stratify the forest area based on structural variation. Sample plots were selected to maximize the range of tree heights and densities. This design enabled a comprehensive representation of the diverse stand types found in Evo, including managed young forests, mature single-layered stands, and structurally complex old growth forests. The datasets consisted of squared plots (32 × 32 m, 37 plots in **Study I**) and circular plots of varying sizes (99 plots with a 20 m radius in **Study II**, and 49 plots with a 15 m radius in **Study III**). In **Study I**, conventional field measurements of tree DBH and species were conducted for each plot, whereas **Studies II and III** were based exclusively on laser scanning data. From these measurements, the Gini index was calculated to describe DBH variability, and the Shannon index was used to characterize tree species diversity. The sample plots were further stratified into three categories based on species composition and DBH variation. Although the plot shapes and sizes differed, many of the plots overlapped spatially across the studies. Plot locations were measured using either a Trimble GEOXM GNSS receiver or a Trimble 5602 total station, which was oriented with ground control points obtained using VRS-corrected GNSS (Trimble R8), depending on the dataset.

2.2 Laser scanning data collection and processing

2.2.1 *Study I: Low-density airborne laser scanning data collection and preprocessing*

This study employed bi-temporal ALS data to assess changes in forest structural complexity over time. The data were acquired through Finland's national laser scanning program, which ensures standardized quality and spatial accuracy across all acquisitions (National Land Survey of Finland, 2025). Two ALS datasets, representing the years 2012 and 2019, were selected for analysis. Both datasets were collected in early May under similar environmental conditions, ensuring consistency in canopy reflectance and minimizing variation caused by seasonal foliage differences. The 2012 data were obtained on May 13 using two different laser scanning systems. A Leica ALS50 sensor was used for part of the study area from an altitude of 2200 m, producing a point density of approximately 0.80 pts/m². The remaining area was scanned using an Optech ALTM Gemini sensor at a lower altitude of 1830 m, resulting in a point density of about 0.74 pts/m². The 2019 data, collected on May 6, were acquired using a Riegl VQ-1560i sensor from an altitude of 1755 m, producing a point density of approximately 0.50 pts/m². Despite differences in sensor models and acquisition parameters, both datasets conformed to the specifications set by the National Land Survey of Finland, with a mean point spacing of approximately 1.4 m and an elevation accuracy of 15 cm. Preprocessing of the ALS data involved spatially aligning the point clouds and clipping them to match the boundaries of the 37 sample plots used in the study.

2.2.2 *Study II: Airborne- and terrestrial laser scanning data collection and preprocessing*

TLS data were collected between April and May 2021 using a Leica RTC360 time-of-flight scanner. Each 20-meter-radius sample plot was scanned from nine locations—one at the center and eight evenly spaced around the edge. This setup minimized occlusion and provided a complete ground-level view of the vegetation. The scanner operates at a 1550 nm wavelength and produces dense, high-resolution point clouds with sub-centimeter accuracy. To ensure precise alignment, all scans were registered in Leica Cyclone Register360 (Leica Geosystems, Balgach, Switzerland) software using five to six spherical reference targets placed around each plot. Helicopter borne ALS data were acquired on June 22, 2021, at a flying altitude of 80 m and a flying speed of 50 km/h. The scanning system included three Riegl laser scanning units—VUX-1HA, MiniVUX-3UAV, and VQ-840-G—working simultaneously. This setup resulted in point clouds, with an average density of 1 800 pts/m². Flight trajectories were processed using Inertial Explorer software (NovAtel Inc., Canada) with differential GNSS correction from a nearby base station. Final registration and quality control were done in RiProcess (Riegl Laser Measurement Systems GmbH, Austria) software. Before analysis, both TLS and ALS point clouds were clipped to a 25-meter radius around each plot to ensure full coverage of tree crowns, especially those near the plot boundary. The point clouds were height-normalized using a digital terrain model created with the lasground tool in LAStools (rapidlasso GmbH, Gilching, Germany). From the normalized data, canopy height models (CHMs) were generated at a 0.5-meter resolution. This resolution was selected to reduce noise while maintaining sufficient detail, based on validation from previous studies at the same site. Individual tree detection (ITD) was performed using a marker-controlled watershed segmentation of the CHMs. Local maxima were identified using a variable window size scaled to tree height, improving the detection of differently sized trees. Individual tree segmentation was then carried out using the Dalponte2016

algorithm (Dalponte & Coomes, 2016), which assigned point cloud data to each tree crown based on the CHM and tree locations. For object-level analysis, only trees with tops located within the 20-meter plot radius and crowns fully contained within the 25-meter buffer were included. For grid-level analysis, each plot was divided into six equal sectors to measure intra-plot variability in structural complexity. This approach allowed direct comparisons of horizontal, vertical, and volumetric complexity metrics between TLS and ALS. By following standardized data acquisition and preprocessing procedures for both scanning methods, this study ensured a consistent and reliable comparison of forest structural complexity across different sensing platforms and analysis scales.

2.2.3 Study III: Multimodal bitemporal laser scanning data collection and preprocessing

To evaluate forest structural complexity development over a 7–10-year period, we utilized four distinct laser scanning datasets that varied in data acquisition geometry and point cloud density: low-density ALS (0.4–1 pts/m²), medium-density ALS (15–28 pts/m²), high-density ALS (200–3 600 pts/m²), and TLS (20 000–24 000 pts/m²). Each dataset captured forest structure from two time points (T1 and T2) within a consistent set of 49 circular sample plots (15 m radius) located in Evo, Southern Finland. Low-density ALS data were acquired in 2012 and 2019 using a Leica ALS50 (T1) and a Riegl VQ-1560i (T2) scanner. The 2019 dataset was thinned to match a uniform density of 1 pts/m² using TerraScan (Terra Solid, Helsinki, Finland), ensuring spatial consistency. Both datasets had similar accuracy characteristics, with elevation RMSE around 15 cm and planar accuracy within 60 cm. Medium-density ALS data consisted of 2009 (T1) and 2019 (T2) acquisitions. The 2009 data were collected using a Leica ALS50-II from 400 m altitude, achieving a density of 28 pts/m². The 2019 dataset matched the low-density ALS acquisition campaign but was analyzed in its original form (15 pts/m²), allowing direct comparison with medium-resolution ALS from 2009. High-density ALS data were captured in 2014 and 2021 using helicopter-borne Riegl sensors. The 2014 T1 dataset (Riegl VQ-480-U) provided 200 pts/m², while the 2021 T2 campaign integrated three scanners—VUX-1HA, MiniVUX-3UAV, and VQ-840-G—operated simultaneously from 80 m altitude at 50 km/h, yielding point densities up to 3600 pts/m². This configuration enabled detailed three-dimensional canopy reconstructions. TLS data were collected in 2014 and 2021 using a combination of phase-shift (HDS6100, Faro Focus 3D) and time-of-flight (Leica RTC360) scanners. A multi-scan setup was applied, with five scans per plot in 2014 and nine scans per plot in 2021. All scans were co-registered using Leica Cyclone Register360 and spherical reference targets (five to six per plot). Point clouds were down sampled to a 3 cm point spacing using LAsTools to maintain consistency in resolution and enhance processing efficiency. For all datasets, plot-level point clouds were clipped to a 15 m radius and height-normalized using the lasground tool in LAsTools to remove topographic variation. This standardization ensured vertical alignment across data sources and enabled generation of CHMs at appropriate resolutions (2 m for low-density, 1 m for medium-density, 0.5 m for high-density ALS and TLS). These CHMs were then used as a basis for individual tree detection (ITD), segmentation, and subsequent structural complexity metric calculations. The ITD procedure was conducted similarly to the approach described in Section 2.2.2 (**Study II**). This harmonized multi-sensor data acquisition approach allowed for systematic evaluation of how different laser scanning techniques and point cloud characteristics influence the observed trends in forest structural complexity.

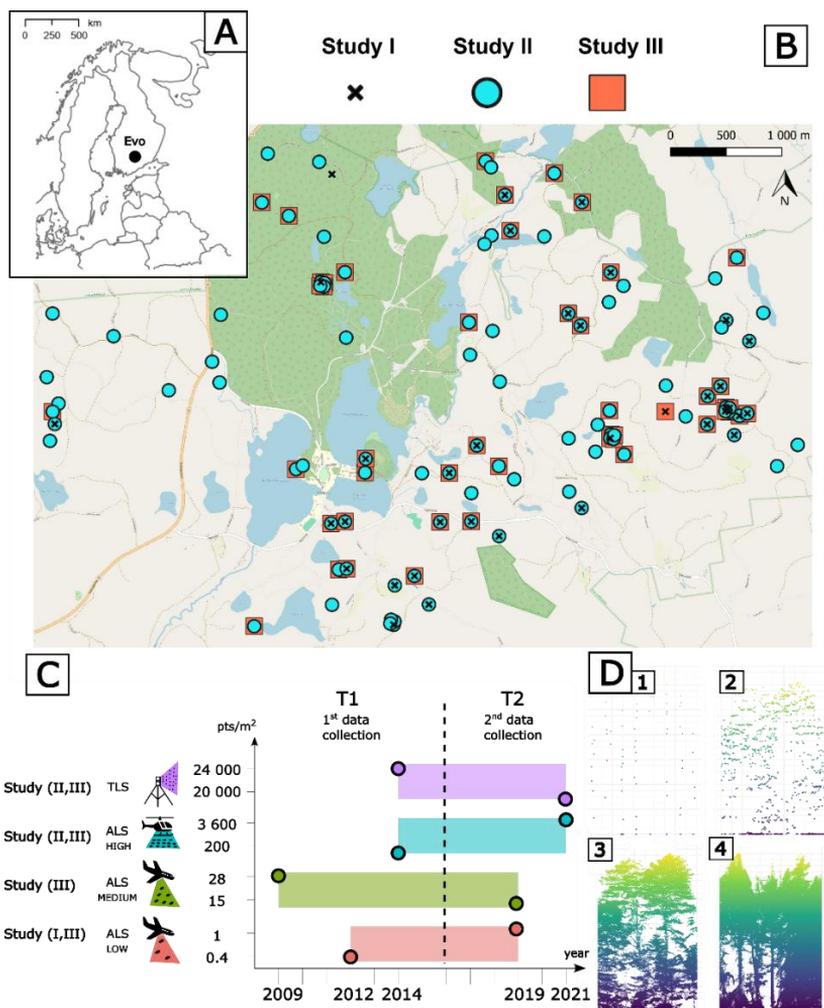


Figure 1. (A) Location of study plots in Evo, Finland, northeastern Europe; (B) distribution of sample plots within the Evo area ($61^{\circ}11'48.87''\text{N}$, $25^{\circ}6'27.9''\text{E}$); (C) summary of laser scanning datasets collected in Evo and used in this dissertation; (D1–D4) examples of point cloud data showing forest stand structure from (1) low-, (2) medium-, (3) high-density ALS, and (4) TLS data.

2.3 Laser scanning-based metrics to estimate forest structural complexity

In the thesis, laser scanning-based structural complexity metrics were calculated considering vertical, horizontal, and volumetric dimensions. These metrics were derived using four approaches: grid-based metrics from the canopy height model (CHM), grid-based metrics from raw laser scanning point clouds, object-level metrics from the CHM, and object-level metrics from raw point clouds within individual tree segments. To summarize structural complexity metrics used in the thesis were categorized into two groups: 1) two-dimensional and 2) three-dimensional metrics.

2.3.1 Two-dimensional structural complexity metrics

Two-dimensional metrics are derived within horizontal (x, y) spatial units—such as grid cells (e.g., CHM) or individual crown segments—where the vertical (z) structure is summarized within these two-dimensional areas. CHM-based metrics were derived from rasterized point clouds and provided information on both vertical and horizontal forest structure. The CHM-based approach provided a standardized method for assessing structural complexity across different forest conditions and sensor types. Mean Canopy Height was calculated as the average of all non-zero CHM values within a plot (**Study II, III**). This metric provided a straightforward measure of average stand height and served as a general indicator of forest maturity; larger CHM values indicate a greater potential for higher structural complexity. Canopy Rugosity was computed as the standard deviation of CHM values across the plot (**Study III**). It reflected the roughness or texture of the canopy surface, with higher values indicating a more irregular and vertically diverse canopy structure. Canopy Cover was defined as the proportion of CHM raster pixels exceeding a height threshold of three meters relative to the total number of CHM pixels in the plot (**Study II**). This horizontal metric captured the extent of canopy occupancy and was used to evaluate the density and spatial coverage of the forest canopy.

In addition to CHM-based metrics, this thesis employed grid-based metrics calculated directly from the raw laser scanning point cloud. These metrics offered complementary insights by capturing the detailed distribution of laser returns in both horizontal and vertical dimensions within the plots. Horizontal structural complexity was assessed using the gap fraction (**Study III**). This metric was defined as the proportion of laser scanning returns falling below a 2-meter height threshold relative to the total number of returns in a plot. A higher gap fraction indicated a more open canopy, where more laser pulses penetrated to the understory or ground layer, suggesting a fragmented or discontinuous horizontal structure. Vertical structural complexity was evaluated using Shannon entropy, a metric that describes the evenness of the vertical distribution of laser scanning returns (**Study III**). Each plot was divided into ten equal-height vertical layers based on its maximum canopy height, and the relative frequency of points in each layer was used to compute the entropy value. Higher Shannon entropy indicated a more even vertical layering of vegetation - characteristic of complex forest stands with multiple strata.

Beyond grid-based approaches, the thesis also included object-level structural complexity metrics derived from segmented individual trees. These metrics focused on variation in tree size and form within plots, reflecting ecological processes such as competition, growth dominance, and resource allocation. Two statistical approaches were used to describe both vertical and horizontal structure: the coefficient of variation (CV) and the Gini index. Vertical structural complexity at the object level was evaluated using tree height, but it was assessed differently in the two studies. In **Study II**, vertical complexity was measured using the coefficient of variation of individual tree heights. Heights were estimated from segmented crown data, and the CV of these values across each plot described the variability in tree height. High CV values indicated considerable variation in tree height, suggesting a vertically heterogeneous stand structure. In **Study III**, vertical complexity was described using the Gini index of tree heights, which captured the degree of inequality in tree size distribution. High Gini values denoted plots where a few tall trees dominated, while most others remained short—indicating strong vertical asymmetry. Horizontal structural complexity was similarly characterized using variation in tree crown areas. In **Study II**, the coefficient of variation of crown areas was used to evaluate the diversity in tree crown sizes within each plot. Larger

CV values indicated greater disparity in crown sizes, pointing to uneven resource acquisition or structural variability. In **Study III**, the Gini index of crown areas was employed as an alternative measure of inequality, highlighting how dominant trees might occupy disproportionately large horizontal space. High Gini values suggested strong horizontal heterogeneity, with significant differences in crown size between individuals.

2.3.2 *Three-dimensional structural complexity metrics*

In addition to two-dimensional grid-based and object-level structural metrics, this thesis incorporated volumetric complexity metrics to capture three-dimensional aspects of forest structure. These metrics reflect how vegetation occupies space at both the plot scale and the individual tree level, providing insights into canopy architecture, light interception, and resource distribution. **Study I** analyzed temporal changes in stand structural complexity using ALS point clouds from 2012 and 2019. Canopy vertical profiles (CVPs) were generated to describe canopy layering and light availability. Point clouds were clipped to plot boundaries and divided into $4 \times 4 \times 1$ m voxels. Voxels were classified into four categories based on vegetation presence and position relative to the 65th height percentile: empty voxels above the threshold were considered open gaps, empty voxels below it were closed gaps, occupied voxels above it were euphotic zones, and occupied voxels below it were oligophotic zones. The resulting CVPs summarized the vertical proportions of open gaps, closed gaps, and canopy layers for each plot. **Studies II** and **III** used the filled voxel proportion metric to assess volumetric complexity at the grid level. Each plot was subdivided into three-dimensional cubic voxels covering the height range from 1 m above the ground to 80% of the maximum canopy height. A voxel was considered occupied if it contained at least one laser return. The filled voxel proportion was calculated as the ratio of occupied voxels to the total voxel count, representing how effectively vegetation occupied three-dimensional space. Higher values indicated denser, more structurally complex canopies, whereas lower values reflected sparser stands with greater openness.

At the object-level, volumetric complexity was further assessed using fractal analysis based on the box-dimension metric (**Study II, III**). Box-dimension quantifies the architectural complexity of individual trees by analyzing how point cloud details scale across different levels of spatial resolution. For each segmented tree, a series of voxel grids of varying sizes was generated, and the number of voxels required to enclose the tree's point cloud at each resolution was counted. By plotting the natural logarithm of the number of occupied voxels against the natural logarithm of the inverse voxel size, the box dimension was estimated as the slope of the resulting linear relationship. A higher box dimension value indicated a more complex tree architecture, characterized by a greater degree of branching and spatial occupation across multiple scales. The box dimension thus integrated information about both vertical and horizontal structure within a single value. For plot-level characterization, the mean box dimension and the coefficient of variation of individual tree box-dimensions were calculated, providing measures of average architectural complexity and its variability within the stand. This approach allowed the assessment of intra-plot diversity in three-dimensional tree forms and complemented other measures of structural complexity used in this thesis.

2.4 Analysis

2.4.1 *Assessing structural complexity changes in time using low-density ALS (Study I)*

In **Study I** voxels were classified into one of four light availability categories—open gap, closed gap, euphotic, or oligophotic—based on the 65th height percentile and the presence or absence of ALS returns. Voxels above this threshold represented upper canopy zones (open if no return, euphotic if occupied), while voxels below it represented shaded lower canopy layers (closed if empty, oligophotic if occupied), following the light availability framework proposed by Lefsky et al. (1999). The CVPs summarized the proportions of voxels belonging to each canopy layer category, enabling the assessment of temporal changes in vertical canopy structure. Forest plots were stratified according to structural variability (low, medium, and high tree height variation) and species composition (low- and high-richness conifer-dominant and deciduous-dominant types). To visualize and quantify canopy dynamics, flux graphs were generated to illustrate proportional changes (%) among the four canopy categories between 2012 and 2019, highlighting transitions across forest types and structural complexity levels. The statistical significance of these temporal differences was evaluated using permutation tests for compositional data, accounting for the interdependence among canopy layer proportions.

2.4.2 *Comparing structural complexity estimates derived using TLS and ALS (Study II)*

In **Study II**, forest structural variability was assessed using both object-level and grid-level metrics to evaluate the capacity TLS and helicopter-borne laser scanning (heli-ALS) data to describe forest structure. At the object level, individual tree segmentation was applied to identify and extract structural metrics from each tree. For every segmented tree, crown area was used to represent horizontal structure, tree height to describe vertical structure, and box-dimension to quantify volumetric complexity based on the voxel distribution within each tree's point cloud. The coefficient of variation (CV) for these three metrics was calculated at the plot level to express variability among trees, representing object-level horizontal, vertical, and volumetric structural complexity.

At the grid level, each sample plot was divided into six equal-sized sectors, allowing the examination of intra-plot heterogeneity in canopy structure. Within each sector, mean canopy height and canopy cover were computed individually. The CV across the six sector values of mean canopy height indicated vertical structural complexity, while the CV of canopy cover described horizontal structural complexity, reflecting the evenness of canopy distribution within the plot. Volumetric complexity at the grid-level was evaluated using voxel-based vegetation occupancy derived from height-normalized point clouds filtered between 1 m and 80% of the stand height to minimize the influence of scanning geometry differences between TLS and heli-ALS. The CV of vegetation occupancy among the six sectors was used to quantify grid-level volumetric complexity.

Statistical comparisons between TLS and heli-ALS, as well as between object- and grid-level metrics, were conducted using F-tests to evaluate differences in variability ranges. Additionally, Spearman's rank correlation and R^2 values were applied to assess the level of agreement and consistency of structural complexity metrics across the different data sources and analysis methods.

2.4.3 *Assessing structural complexity development using different laser scanning techniques (Study III)*

In this study, forest structural complexity development was assessed over a multi-year period using four laser scanning techniques across boreal forest plots in Evo, Southern Finland, and evaluated using a set of eight structural complexity metrics: mean canopy height, canopy rugosity, gap fraction, vegetation occupancy (filled voxel proportion), vertical evenness (Shannon entropy), Gini coefficients of height and crown area, and mean tree box-dimension. Each scanning method was evaluated at two time points (T1 and T2), and changes in metric values were used to assess structural development. Comparisons focused on whether different techniques and analysis methods yielded similar significance, direction, and magnitude of structural changes. Paired t-tests and Wilcoxon tests were used for within-method comparisons, while cross-method agreement was assessed by testing whether metric trends between techniques were statistically similar.

3 RESULTS AND DISCUSSION

3.1 **Low-density ALS enables reliable forest structural complexity monitoring over time (Study I)**

Bi-temporal low-density ALS data (<1 pt/m²) proved effective for detecting structural changes in southern boreal forests over a seven-year monitoring period. Despite the sparse point density, voxel-based CVPs similar to studies by revealed clear trends in vertical canopy development, layering, and light availability, demonstrating that national-scale ALS datasets can provide ecologically relevant insights into forest structural dynamics. Forest stands with higher initial structural complexity—characterized by greater tree height variability, deciduous dominance, and higher species richness—exhibited more pronounced changes between 2012 and 2019. The proportions of vegetated canopy layers (euphotic and oligophotic) increased consistently across all plots over time, while the amount of non-vegetated space below the canopy (closed gap) declined (Figure 2). Closed gap ratios were consistently higher in more complex stands, and this relationship persisted throughout the monitoring period. Both euphotic (photosynthetically active) and oligophotic (photosynthetically less active) canopy layers expanded at similar rates across all structural complexity categories. This parallel development likely reflects the relatively short observation period in the context of boreal tree lifespans, during which distinct long-term differences between forest types did not yet emerge. Stands with greater structural complexity also showed higher voxel classification turnover, indicating more dynamic canopy reorganization. Filled voxel proportions (euphotic and oligophotic zones combined) increased by 12.2%, 14.4%, and 18.6% in plots with low, medium, and high height variability, respectively. Similarly, increments across species richness categories were 11.9%, 17.0%, and 18.1%. These results confirm that structurally diverse stands undergo stronger vertical reorganization and canopy infilling than simpler stands. By contrast, the ratio of open gaps above the canopy remained largely unchanged, with no statistically significant differences detected between 2012 and 2019. Although increases were observed in deciduous-dominated plots, the small number of such stands prevented these changes from

reaching statistical significance. Despite limitations related to the small sample size (37 fixed 32×32 m plots), unbalanced stratification due to few deciduous-dominated stands, and minor variation in ALS point density between acquisitions, the study demonstrates the feasibility of using national ALS datasets for monitoring forest structural change. Such datasets hold considerable potential for large-scale ecological applications, including the identification of structural complexity hotspots and the characterization of forest development trajectories under varying boreal stand conditions.

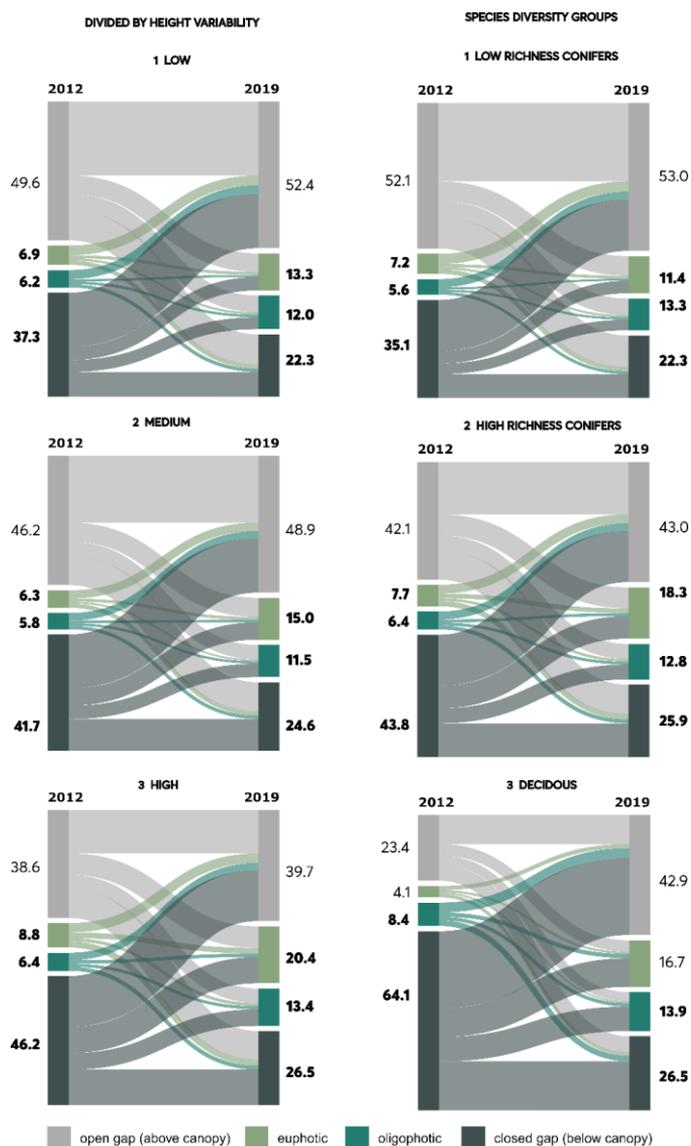


Figure 2. Flux graphs summarize the traced proportional changes (%) in between the canopy layering structures across different forest types, stratified into three structural complexity categories (complexity increases top-down) based on sample plot-level tree height variability and species diversity. Percentage values in bold had statistically significant differences between 2012 and 2019 ($p > 0.05$).

3.2 Object-level assessments enhance in detection of vertical and horizontal forest complexity (Study II)

In this study, we compared TLS and heli-ALS for assessing forest structural complexity, focusing on both object-level and grid-based metrics. We measured two-dimensional (horizontal and vertical) and three-dimensional (volumetric) indicators of stand structure and evaluated metric variability across plots using the CV as a measure of sensitivity.

Overall, TLS did not capture statistically significantly larger variability than heli-ALS for most metrics. The exception was the object-level volumetric box-dimension metric, where TLS showed a statistically broader CV range, reflecting its ability to capture fine-scale understory structures, as this density-demanding method benefits from the higher detail of TLS point clouds (Figure 3). In general, object-level metrics captured a broader range of CV variability than grid-level metrics, with the exception of the filled voxel proportion (volumetric grid metric). The object-level box-dimension metric describes the architectural variability of individual trees and is sensitive to fine-scale heterogeneity, but its reliability can be reduced by difficulties in detecting smaller or occluded trees, which may reduce the variability. In contrast, the grid-level voxel approach quantifies vegetation occupancy without requiring individual tree detection. This makes it less dependent on point cloud density and better suited to capture consistent variability in volumetric complexity across different datasets.

When comparing sensor agreement, volumetric metrics exhibited the lowest correspondence. The object-level box-dimension metric had very low agreement between TLS and heli-ALS ($R^2 = 0.04$), while the grid-based filled voxel proportion performed slightly better ($R^2 = 0.40$). These discrepancies can be attributed to acquisition geometry: TLS, with its bottom-up perspective, captures fine-scale lower canopy elements, whereas heli-ALS mainly describes upper canopy surfaces. For two-dimensional structural complexity metrics, the patterns were mixed. For horizontal complexity, the object-level crown area variability showed stronger agreement ($R^2 = 0.66$) than the grid-level canopy height model (CHM) variability ($R^2 = 0.46$). In contrast, for vertical complexity, the grid-based canopy cover metric had slightly higher agreement ($R^2 = 0.58$) than the object-level tree height variability ($R^2 = 0.57$).

These results demonstrate that object-level metrics are more sensitive in describing forest structural heterogeneity, particularly when dense, high-quality laser scanning data are available. However, grid-based metrics such as filled voxel proportion remain more robust across platforms and are less affected by acquisition geometry. From a practical perspective, heli-ALS provides a scalable option and was able to capture variability comparable to TLS, making it a useful alternative for stand- and landscape-level monitoring and well suited for integration into national forest inventory programs. TLS adds value when the box-dimension metric is applied, as it captures detailed understory and habitat-related structures that are especially relevant for biodiversity assessments.

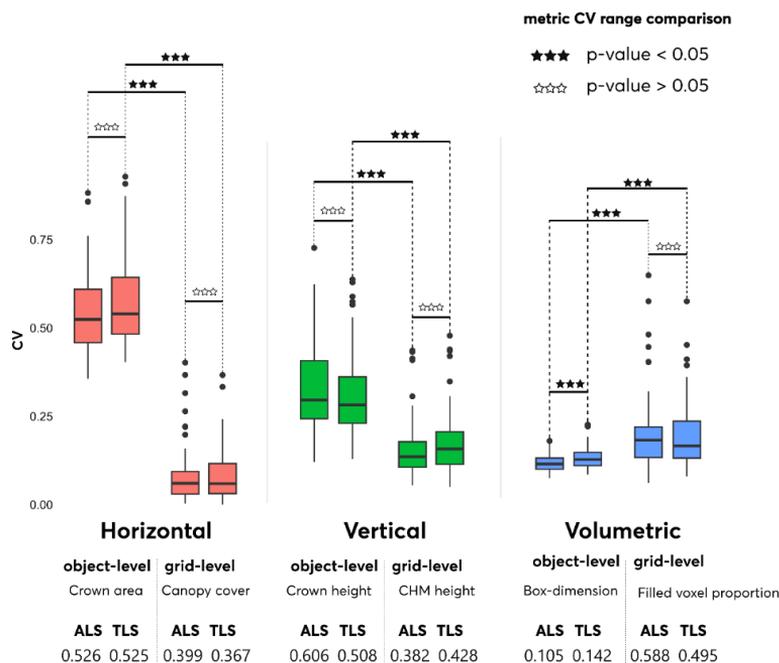


Figure 3. Comparison of the captured range of variability, measured as the coefficient of variation (CV), in horizontal, vertical, and volumetric structural complexity metrics calculated using object-level and grid-level approaches between helicopter-borne laser scanning (heli-ALS) and terrestrial laser scanning (TLS).

3.3 Structural complexity metric consistency and robustness varies with point cloud density and data acquisition geometry (Study III)

The ability to monitor forest structural complexity development depends strongly on both the selected analysis method and the characteristics of the applied laser scanning technique. Among the eight investigated metrics, CHM, gap fraction, and Shannon entropy provided the most robust observations across sensors and point densities, as they showed consistent development trend directions and only insignificant differences in metric values between T1 and T2 (Figure 4 and Figure 5). Gap fraction consistently decreased, suggesting canopy closure and reduced heterogeneity, while Shannon entropy increased, reflecting more even vertical distribution of vegetation over time. These complementary trends highlight that structural complexity may evolve differently in vertical and horizontal dimensions, stressing the need for multidimensional assessment.

Volumetric metrics, in contrast, showed greater sensitivity to point cloud density and acquisition geometry. Box-dimension values derived from low- and medium-density ALS often fell below their theoretical threshold, confirming their limited suitability for individual tree level volumetric assessments. TLS, however, provided reliable box-dimension estimations, capturing increased architectural detail and understory structures essential for biodiversity and habitat monitoring. Filled voxel proportion proved more robust than box-dimension but displayed varying development trends across datasets, suggesting sensitivity to acquisition parameters rather than purely structural changes. Discrepancies between

metrics highlight that single indicator cannot fully describe the dynamics of forest structural complexity. Horizontal canopy closure and vertical layering may evolve in contrasting directions, while volumetric measures often reflect acquisition parameters as much as actual forest changes. A multi-metric approach that integrates robust horizontal, vertical, and volumetric indicators, complemented by calibration and potentially machine learning based metric harmonization, offers potential for long-term monitoring of forest structural complexity across diverse conditions and datasets.

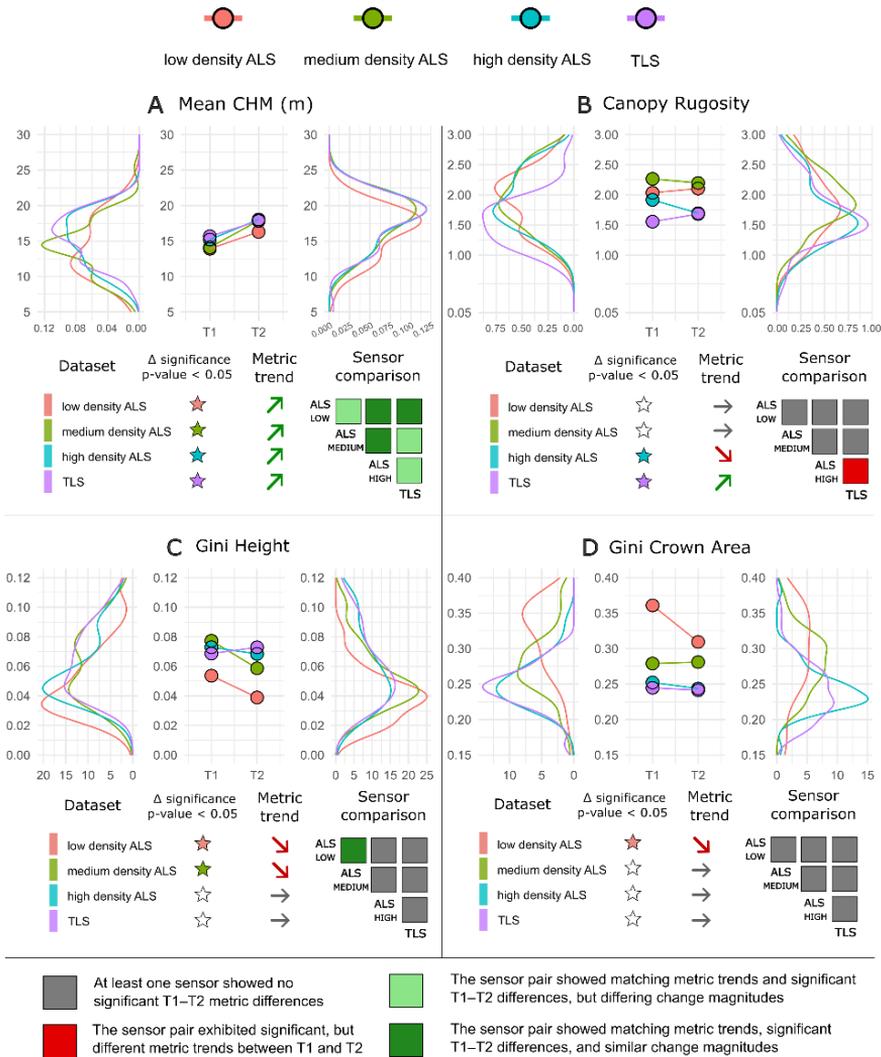


Figure 4. Summary of changes in structural complexity metrics between two data acquisitions (T1 and T2) across 49 sample plots when derived using four different laser scanning techniques: low-density, medium-density, and high-density airborne laser scanning (ALS) and terrestrial laser scanning (TLS). 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 coloring.

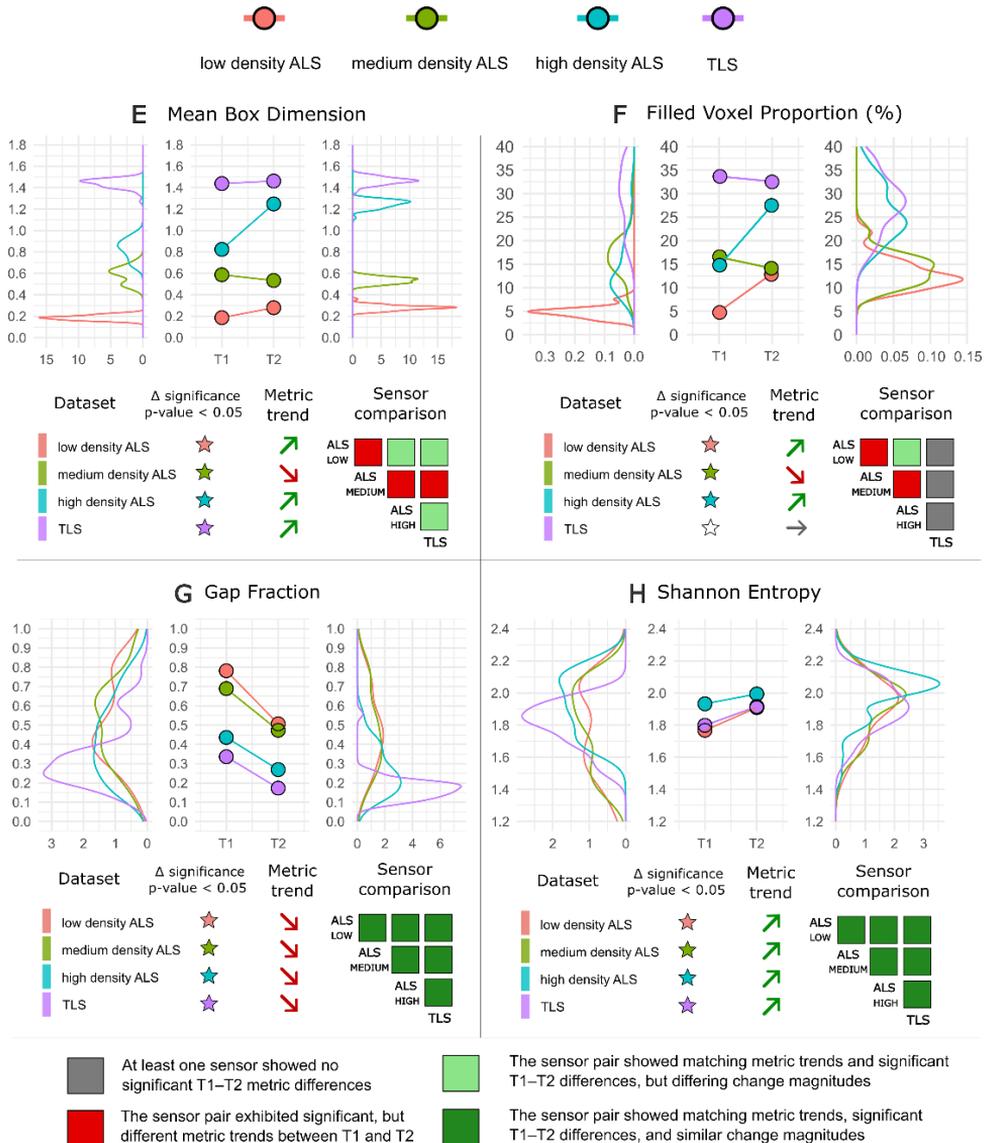


Figure 5. Summary of changes in structural complexity metrics between two data acquisitions (T1 and T2) across 49 sample plots when derived using four different laser scanning techniques: low-density, medium-density, and high-density airborne laser scanning (ALS) and terrestrial laser scanning (TLS). 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 coloring.

4 CONCLUSIONS

To better understand the forest ecosystem dynamics, accurate and consistent observations of structural characteristics over time are essential. Monitoring the development of forest structural complexity is a key aspect of understanding ecological processes, resource distribution, and habitat quality. Therefore, this thesis assessed the feasibility and reliability of laser scanning technologies for monitoring forest structural complexity across spatial and temporal scales, providing insights into their applicability for ecological research and forest management. The first objective was to examine whether low-density airborne laser scanning (ALS) data reliably detect temporal changes in forest structural complexity, particularly regarding vegetation occupancy and light penetration. **Study I** demonstrated that even sparse ALS data (<1 pts/m²) can reliably detect meaningful changes in canopy structure in southern boreal forests, particularly through voxel-based analysis methods such as CVPs. The results revealed that changes in light penetration, canopy layering, and vegetation occupancy could be consistently captured over a seven-year period. Forest stands with initially higher structural complexity exhibited stronger development trends, emphasizing the role of initial diversity in shaping long-term structural change. These findings highlight the value of national ALS datasets for large-scale ecological monitoring and suggest that even coarse, cost-efficient data sources can support ecological research and forest management when analyzed with suitable methods.

The second objective was to evaluate and compare structural complexity metrics derived from ALS and TLS data at object and grid levels across vertical, horizontal, and volumetric dimensions. **Study II** demonstrated that object-level metrics, based on individual tree segmentation, provided a more detailed and sensitive description of vertical and horizontal complexity than grid-level metrics based on canopy models. Both TLS and high-density heli-ALS effectively captured structural variability, although differences in data acquisition geometry led to lower agreement in volumetric complexity estimates. Nevertheless, grid-level volumetric metrics such as filled voxel proportion offered a scalable alternative and showed better agreement between TLS and heli-ALS. Almost all metric CV ranges were not statistically significantly different, indicating that sensor selection and acquisition geometry had only minor influence on most results. These findings demonstrate that object-level approaches are especially relevant for biodiversity and habitat-related applications, while grid-level approaches are more practical for robust integration into forest inventory systems.

The third objective was to assess point cloud density and scanning geometry influence the consistency and robustness of forest structural complexity metrics across different laser scanning datasets. **Study III** showed that two-dimensional metrics—such as Shannon entropy, gap fraction, and mean canopy height—were highly robust and produced consistent results across laser scanning systems and point cloud densities. These metrics are suitable for long-term forest monitoring, even if data from laser scanning sensors were combined. In contrast, three-dimensional and volumetric metrics such as box-dimension and filled voxel proportion were more sensitive to point cloud characteristics and scanner geometries, limiting their comparability across platforms unless very high point densities were available. This emphasizes the importance of metric selection, calibration for enabling reliable cross-sensor monitoring.

Overall, the findings of this thesis strengthen the understanding of how point cloud-based methods can be used to characterize forest structural complexity across space and time.

These results emphasize that laser scanning technologies, when appropriately applied and carefully interpreted, provide non-destructive, repeatable, and objective measurements that enhance our capacity to monitor and understand forest ecosystems. By enabling direct observation of forest structural dynamics without reliance on destructive field methods, point cloud-based approaches contribute to advancing ecological research, supporting precision forestry, and informing biodiversity conservation strategies. Consequently, the continued development and application of laser scanning methods are expected to play an increasingly important role in improving our understanding of forest structure, function, and resilience under changing environmental conditions.

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