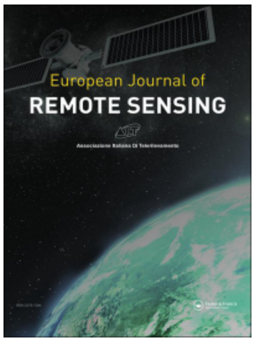

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Quantifying changes in forest structural complexity using bi-temporal airborne laser scanning

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ABSTRACT

Structural complexity is an important forest characteristic for habitat assessment, forest management and planning. However, monitoring how forest structural complexity evolves over time in various forest types has not been widely explored. In this study we investigate the feasibility of bi-temporal low-density airborne laser scanning (ALS) for the assessment of changes in light availability conditions within forest canopy, considered to imply changes in forest structural complexity. We used ALS data acquired in 2012 and 2019 to generate canopy vertical profiles by slicing the point clouds into 4 × 4 ×1 m voxels which were then rasterized and reclassified into four light availability categories. To understand structural development over time in different forest types we used field-measured tree heights and tree species information to stratify sample plots in different stand complexity categories. Stands with higher structural complexity represented increased proportions of space occupied by vegetation as well as decreased proportions of empty space below the canopy. The experiments showed the ability of low-density ALS to characterize the dynamics in canopy layering structure, implying changes in forest structural complexity. The presented methodology could potentially be upscaled and applied in the landscape-level monitoring of the development of boreal forest structural characteristics.

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ALS; LiDAR; canopy vertical profile; forest monitoring; forest structural complexity

Introduction

Forests are complex ecosystems where the co-existence of different species in changing environmental conditions form varying forest structures (Ehbrecht et al., 2021). Trees are the largest species in terrestrial ecosystems, and their structural variability is linked to forest structural diversity (Lindenmayer et al., 2000). The structural complexity of a forest stand can be characterized through, e.g. tree size distribution, spatial composition and density of vegetation, species richness, and diversity in crown layering structure (Zenner & Hibbs, 1999). These all are subject to change in time through the growth processes of trees and their interaction with each other, which can be altered through silvicultural activities or by natural disturbances (McElhinny et al., 2005). Understanding how structural complexity is changing through time is valuable information for assessing forest stand functioning (Ali, 2019), habitat quality (Coops et al., 2016) decision-making and forest management planning (Camarretta et al., 2020). However, assessing forest structural complexity and its change is a challenging and laborious task to be conducted over large areas (Ehbrecht et al., 2021).

When based on the assessment of tree size variability, forest structural complexity can be estimated with conventional inventory techniques such as field measurements with callipers and clinometers (McElhinny et al., 2005). For improving measurement scalability, forest structural complexity can be assessed by characterizing the spatial composition, variability and density of vegetation within a forest stand using different remote sensing technologies (Maltamo et al., 2005; Næsset, 1997). These include multispectral satellite imagery (Halme & Mõttus, 2023), airborne (Means et al., 2000) and spaceborne laser scanning (Queinnec et al., 2021) as well as terrestrial laser scanning (Seidel et al., 2021; Yrttimaa et al., 2020). However, the utilized remote sensing technology must have descriptive abilities throughout all the vegetation layers to provide a sufficient characterization of the complexity of the forest structure. Thus, passive remote sensing techniques such as aerial and satellite imagery usually face limitations related to the characterization of vegetation under the dominant canopy layer (Maltamo et al., 2014). Therefore, inner canopy characteristics have been studied using active remote sensing technologies such as airborne laser scanning (ALS) (Bruggisser et al., 2019). ALS has shown to be a feasible technique for forest structural complexity assessment based on different analytical approaches:

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estimation of diameter distributions (Packalén & Maltamo, 2008), analysis of tree size variability using the Gini Coefficient (Valbuena et al., 2016) or the Lorenz curve (Valbuena et al., 2014), canopy height model-based indices (Kukunda et al., 2019; Zenner & Hibbs, 1999), box dimensions (Seidel et al., 2019), Vertical Complexity Index (VCI), Leaf Area Density (LAD), gap fraction profiles and the rumple index (Bouvier et al., 2015; van Ewijk et al., 2011).

Indeed, characterizing the structure of the forest canopy is essential for understanding forest eco-physiology (Ohmann & Spies, 1998) as it hosts the domain for photosynthesis and competitive interactions between tree individuals (Parker & Brown, 2000). In addition to the characterization of solid canopy elements only, inclusion of analysis of the empty space between the tree crowns and how it gets occupied by wood and foliage over time is beneficial for monitoring canopy structural dynamics (Lefsky et al., 1999; Parker et al., 1995). Therefore, assessment of canopy structural characteristics, including the open space and the space occupied by vegetation, and their development in time, can be used for monitoring forest structural complexity.

Canopy vertical profile (CVP) describe the vertical composition of vegetative structures such as stems, branches, and foliage, thereby providing the means for assessing the complexity of forest canopies (Zhang et al., 2017). The CVP approach can be considered as a suitable methodology for structural complexity estimation using sparse ALS data as it describes how the vegetative structures occupy the space and use available resources (Lefsky et al., 1999). In addition of vegetation occupancy analysis, stratification of the canopy by different light availability categories and analysis of changes in related canopy layers gives insights into net primary productivity as well as the capacity of a forest stand for the absorption of photosynthetically active radiation (Parker et al., 1995). The concept of CVP was first described by (Lefsky et al., 1999) where they used a full-waveform profiling laser altimeter to estimate canopy proportions in different light availability categories (i.e. open gap, euphotic zone, oligophotic zone, and closed gap) in different age-class forests of Douglas fir in the USA. Their findings indicated that the vertical distribution of the light availability classes changed with stand age. The filled CVP voxel proportions (i.e. euphotic and oligophotic zones) were decreasing from very young, young, and mature stands, but stayed the same for mature and old-growth stands. Coops et al. (2007) modified the presented approach further Lefsky et al. (1999) and used a discrete-return ALS to create CVPs and found significant correlations among CVP-derived and field-measured stand characteristics in the Coastal Western Hemlock biogeoclimatic subzone in British Columbia, Canada. Similar findings were reported by Zhang et al. (2017) who applied the CVP-based approach to assess the structural characteristics of subtropical forests in China.

Overall, there seems to be feasible technologies such as low-density ALS accompanied with established analysis methods such as CVPs for assessing the canopy layering structure which is associated with forest structural complexity. However (Coops et al., 2007; Lefsky et al., 1999; Maltamo et al., 2014), captured changes in forest structural complexity, but development of canopy structure over time in different forest types have remained less explored. To fill in this knowledge gap, our study aims to investigate how low-density bi-temporal ALS point clouds can be used to characterize changes in forest structural complexity of boreal forests, assessed through the changes in the canopy layering structure. We used ALS-derived CVPs to assess how the canopy layering structure changed during a 7-year monitoring period. We focused on analysing changes in the light availability zones that are expected to imply changes in how vegetation occupies the space (i.e. open gap and closed gap) and use the available resources (i.e. oligophotic and euphotic zones). Particularly, we investigate how the relative proportions of different canopy layers change in time between different forest types. For this task, we categorized the sample plots ($n = 37$) by their field-measured structural complexity based on 1) tree height variability and 2) species richness and analysed CVP differences within the established categories. With these experiments, we aimed to assess the capacity of low-density bi-temporal ALS to reveal changes in canopy structure. The contribution of this study is to improve understanding and feasibility of the applied methodology for forest structural complexity assessment.

Materials and methods

Study site and experimental design

The study site was established in Evo, Hämeenlinna (61°11’48.87”25°6’27.9”) which is located Southern Finland (Figure 1) and belongs to southern boreal biome with dominant tree species of Scots pine (*Pinus sylvestris* L.) and Norway spruce (*Picea abies* (L.) H. Karst.). The terrain is relatively flat with an average elevation of 135 m a.s.l. The experimental design included 37 fixed-size sample plots (32 m × 32 m) distributed throughout the Evo area to capture a wide range of different forest structures (Figure 1).

Conventional field inventories were conducted in 2014 and 2019 for all 37 plots to acquire reference information of the size and location of individual trees (Table 1). For each sample plot, all trees with diameter at the breast height (dbh) > 5

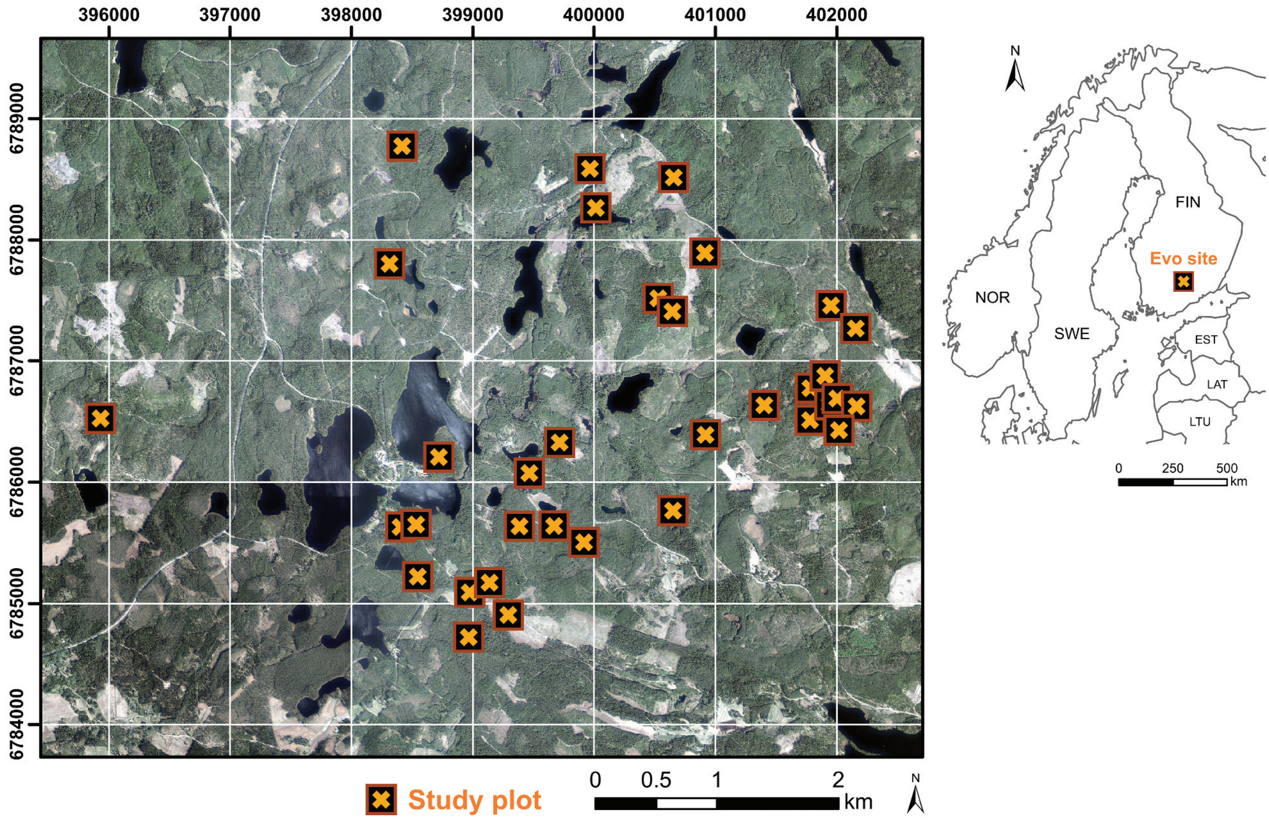

Figure 1. Experimental design included 37 squared sample plots (32 m × 32 m) distributed around Evo, Hämeenlinna in Southern-Finland (61°11′48.87″25°6′27.9″).

Table 1. Summary of plot-level forest structural parameters grouped by year. T1 = 2014; T2 = 2019, plot level forest structural attributes grouped by Gini Coefficient (GC) categories representing the degree of height variability – low (GC < 15), medium (15 < GC < 30), high (GC > 30), as well as by Shannon index categories – group 1 (coniferous plot, Shannon < 0.5), group 2 (coniferous plot, Shannon > 0.5), group 3 (deciduous plot).

		All 37 plots		Gini coefficient category (T1)			Shannon index category (T1)		
		T1	T2	Low (n = 18)	Medium (n = 11)	High (n = 8)	Group 1 (n = 18)	Group 2 (n = 15)	Group 3 (n = 4)
Height (m)	**min**	11.09	12.02	13.37	10.83	11.61	10.83	11.61	13.26
	avg	17.16	18.21	18.71	16.32	12.97	18.02	15.04	15.98
	max	24.78	26.28	24.20	19.99	15.18	21.46	21.54	17.98
Basal area (m^2/ha)	**min**	15.21	16.67	15.21	16.89	23.62	15.21	23.62	17.86
	avg	29.71	32.13	27.12	31.48	33.09	29.24	31.56	24.20
	max	43.17	48.18	36.92	43.17	42.88	41.90	43.17	29.44
Volume (m^3)	**min**	110.61	136.07	128.31	110.61	194.81	110.61	194.81	150.81
	avg	310.68	349.92	296.74	332.85	311.57	326.46	311.12	215.36
	max	510.37	550.93	461.90	510.37	425.47	484.85	510.37	288.45
Number of trees (n/ha)	**min**	341.80	341.80	341.80	527.34	1044.92	341.80	439.45	947.27
	avg	1025.39	997.94	684.14	968.57	2028.81	688.19	1380.21	1606.45
	max	3007.81	2744.14	1660.16	1542.97	3125.00	1542.97	2343.75	3125.00

cm were measured and following tree characteristics were recorded: species, height and dbh. The species was recorded based on visual inspection, tree height was measured using an electronic clinometer, while dbh was determined with calipers as an average of two diameter measurements perpendicular to each other at 1.3 m above the ground. Sample plot locations were measured with global navigation satellite system (GNSS) device GEOXM 2005 (Trimble Navigation Ltd., Sunnyvale, CA, USA), and the locations were postprocessed with local base station data having mean accuracy of 0.6 m. In majority of the sample plots ($n = 24$) the dominant tree species was Scots pine, followed by Norway spruce ($n = 8$). Three sample plots were dominated by birch (*Betula pendula* Roth and *Betula pubescens* Ehrh.) while two plots were occupied by other tree species such as aspen (*Populus tremula*) and fir (*Abies sp.*).

Sample plot stratification based on field inventory data

To have a better understanding about plot heterogeneity and structural complexity we calculated a weighted Gini Coefficient (GC) characterizing variability in tree height distribution within each sample plot based on field inventory data obtained in 2014 (Equation 1; Lexerød & Eid, 2006).

$$GC = \frac{\sum_{j=1}^{n}(2j-n-1)h_j}{\sum_{j=1}^{n}h_j(n-1)} * n \qquad (1)$$

where:

n = number of trees per study plot

h_j = height of the $_j$th tree

j = the rank of a tree in ascending order from 1, . . . , n based on the height

Based on the GC, the sample plots were divided into three categories featuring low (GC < 15, n = 20), medium (15 < GC < 30, n = 8) and high (GC > 30,
n = 9) structural complexity, respectively.

In addition to tree height variation, the sample plots were stratified based on tree species and their variations within the plots using field data from 2014. Firstly, each plot was classified as a deciduous (n = 4) or a coniferous (n = 33) stand based on dominant tree species that featured the highest proportion of total basal area. As most of the plots were coniferous, we aimed at making the stratification more representable and applied a Shannon Equitability index (equation 2) which describes the species evenness within the community (Moreno et al., 2016).

$$H = -\sum_{i=1}^{S} p_i \ln(p_i) \qquad (2)$$

where:

H = the Shannon index value

p_i = the proportion of individuals found in the ith species

ln = the natural logarithm

S = the number of species in the community

With this index we subdivided the coniferous plots into two sub-categories: low species richness (Shannon index < 0.5, n = 18) and high species richness coniferous stands (Shannon index > 0.5, n = 15). Eventually we had three categories based on species distribution and three categories based on height variation which were used to analyze how ALS data captures structural differences and their development over time in structurally different forests, considering tree height variability and species diversity.

Airborne laser scanning data acquisition and pre-processing

To analyze changes in stand structural complexity, we used ALS point clouds acquired in 2012 and 2019. These point clouds are part of national ALS datasets which are openly available and collected throughout Finland following certain data specification and quality requirements (National Land Survey of Finland, 2014). The 2012 ALS data was collected on May 13th using two double-pulse ALS sensors – one part of the study area was covered with a Leica ALS50 (Leica Geosystems, Balgach, Switzerland) laser scanner at a scanning altitude of 2200 m resulting in a point cloud density of 0.8 pts/m^2 while the rest of the study area was covered with an Optech ALTM GEMINI (Teledyne Optech, Toronto, Canada) laser scanner at a scanning altitude of 1830 m and a point density of 0.74 pts/m^2. The 2019 ALS data was collected in 6th of May using a Reigl VQ-1560i (RIEGL, Horn, Austria) laser scanner at a scanning altitude of 1755 m resulting in a point density of 0.5 pts/m^2. Both data sets featured similar quality characteristics – distance between points on the ground was about 1.4 m with a standard error of 15 cm for elevation and ~60 cm in the planar direction. It should be noted that the timing of both ALS campaigns represented similar phenological conditions where the leaf-off season was gradually changing towards leaf-on season, thereby enabling comparable reconstructions of the forest structures.

Assessing canopy layering structure with canopy vertical profiles

We used ALS-derived CVPs to characterize the canopy layering structure in 2012 and 2019. The CVPs were generated by quantifying the occurrence of ALS pulse returns throughout different light availability zones within the canopy. We first clipped both ALS datasets according to sample plot borders (Figure 2a) and sliced the point clouds into 1-m thick horizontal layers. Then the point cloud slices were rasterized using a 4-m resolution thereby representing ALS mean height value within the voxel (Figure 2b).

Each 4 × 4 × 1 m voxel was then assigned a classification representing light availability conditions (i.e. open gap, euphotic zone, oligophotic zone, or closed gap) according to following procedure: If no ALS returns were registered within the voxel, it was considered empty, and the corresponding height raster was assigned a value of zero. Empty voxels locating above the sample plot ′s 65th height percentile was categorized as "open", but if the empty voxel remained below the 65th height percentile then the ALS signal most likely had already returned from upper branches and the canopy category was assigned a classification "closed". The applied threshold at the 65th height percentile was determined by Lefsky et al. (1999) considering the amount of returned energy from the first unit of leaf area index (LAI), assuming an

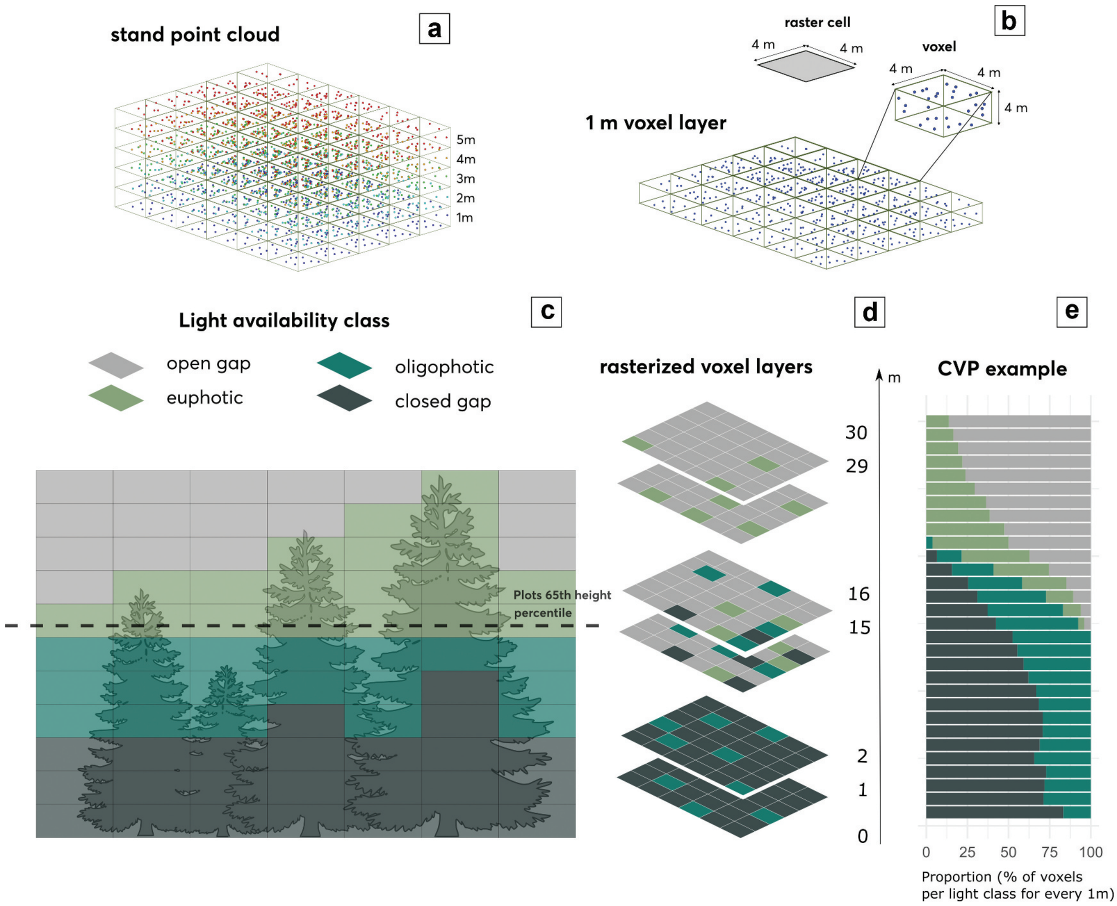

Figure 2. Illustration of the data processing workflow. a) airborne laser scanning point cloud characterizing a sample plot, b) point cloud slicing and voxel rasterization, c) raster reclassification into four light availability classes (i.e. open gap, euphotic zone, oligophotic zone, and closed gap), d) raster stacking, and e) the resulting canopy vertical profile (CVP).

extinction coefficient of 1. When the voxel was not empty, then we assumed that the voxel was occupied by vegetation and at least one ALS return was detected within the voxel. If the occupied voxel located above the 65th height percentile of a sample plot, then it was assigned a classification "euphotic". Otherwise, the non-empty voxels locating below the 65th height percentile were assigned a classification "oligophotic" (Figure 2c). The euphotic and oligophotic categories describe the light availability in the canopy – the euphotic canopy absorbs most of the light, but the oligophotic canopy receives only partial sun radiation (Richards, 1983). Finally, the obtained rasters were stacked (Figure 2d) and the CVPs were generated by summarizing the proportion of voxels with each light category classification within every 1-m point cloud slice (Figure 2e).

Assess how forest structural complexity changes over time in different forest types

We investigated changes in the canopy layering structure during the monitoring period between sample plots stratified based on 1) variability in tree height (i.e. low, medium, and high degree of variation in tree height) and 2) species richness (i.e. low-species richness conifer-dominant, high-species richness conifer-dominant, deciduous-dominant). This involved analysis of differences in the proportions of different light categories (i.e. open, closed, euphotic, and oligophotic) between the CVPs obtained in 2012 and 2019. The statistical significance ($p > 0.05$) of the observed changes was tested with Permutation test (Good, 2013), considering the dependency and compositional characteristics and of the investigated values (i.e. canopy layer proportions that sum up to a constant value). To understand canopy layering dynamics, we also investigated changes in the properties of individual voxels to trace changes in the associated CVP classification over time.

Results

In general, changes in the canopy layering structures followed a similar trend across different forest types (Figure 3). Filled voxel proportions representing the euphotic and oligophotic zones were systematically larger in 2019 compared to the respective canopy

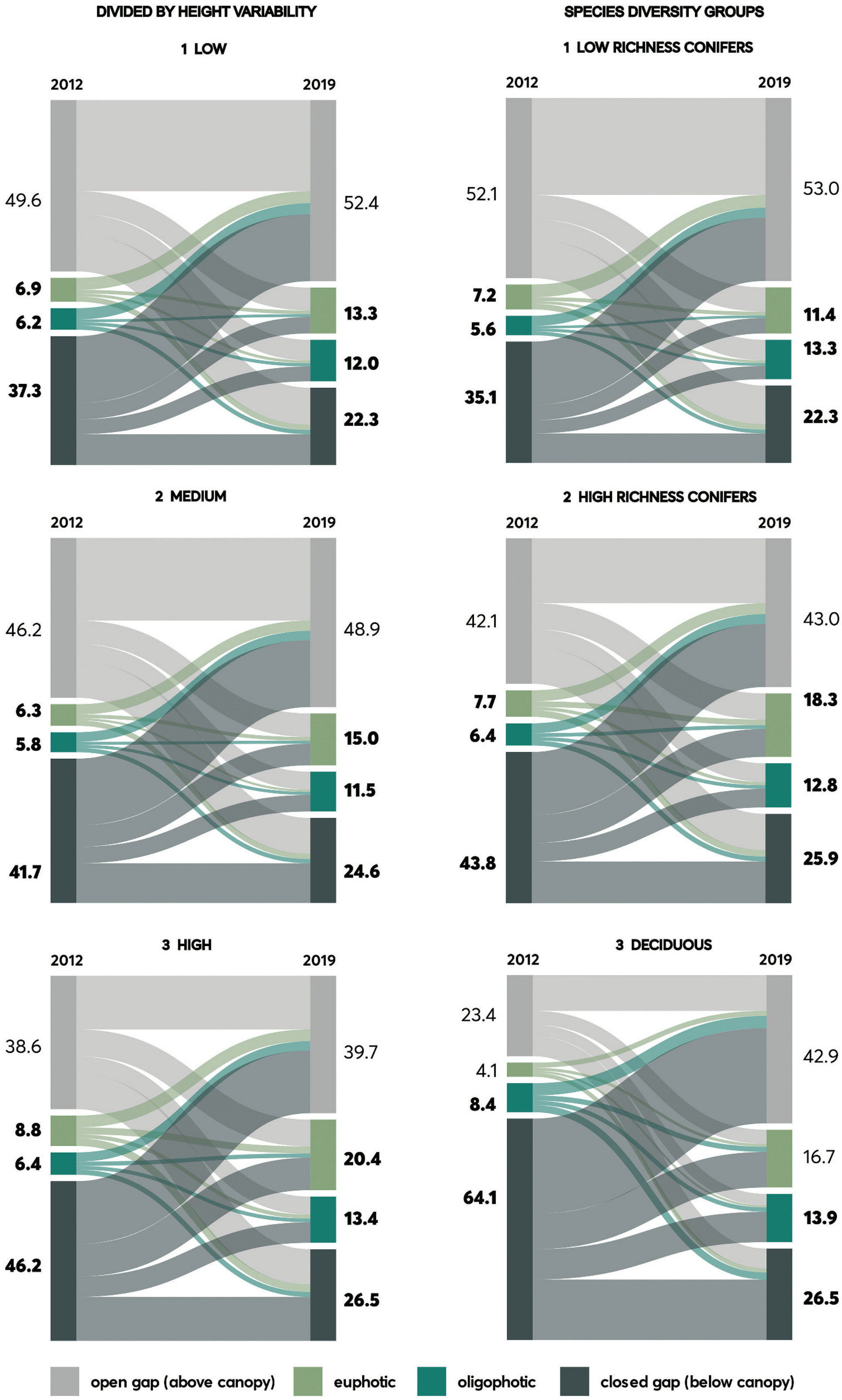

Figure 3. Flux graphs summarising the traced proportional changes (%) in between the canopy layering structures across different forest types, stratified into three structural complexity categories (complexity increases top-down) based on sample plot-level tree height variability and species diversity. Percentage values in bold had statistically significant differences between 2012 and 2019 ($p > 0.05$).

layer proportions in 2012. The closed gap proportion, representing empty space below the canopy, decreased from 2012 to 2019 regardless of the forest type, while the open gap proportion, representing empty space above the canopy, seemed to remain more similar over time. Tracing of the changes in the CVPs revealed variability in the canopy layering structure dynamics across the sample plots: depending on the investigated canopy layer, 4.9% to 66.1% of the voxels exhibited a change in their occupancy properties from 2012 to 2019, leading to a change in the associated canopy layer classification.

Investigation of the canopy layering dynamics within different structural complexity categories revealed that a higher structural complexity was associated with a larger proportional change in the canopy layers from 2012 to 2019 (Figure 3). The filled voxel proportions, representing the euphotic and oligophotic zones combined, increased by 12.2%, 14.4%, and 18.6% for the sample plot categories representing low, medium and high degree of height variability within a forest stand. The respective increments by species richness categories were 11.9%, 17.0%, and 18.1%. The magnitude of change in the closed gap proportions was also associated with an increased structural complexity, as the proportions decreased by 15.0–19.7% and 12.8–37.6% between the height variability and species richness categories, respectively. According to the statistical tests, these differences were considered significant ($p < 0.05$). The open gap proportion usually exhibited moderate increases between 0.9% and 2.8% with deciduous sample plots being an exception with an increase of 19.5%. However, these changes were not considered statistically significant ($p > 0.05$) due to the rather low number of samples in the deciduous dominated sample plots ($n = 4$) and the minority of the observed changes in the rest of the categories.

Discussion

ALS have been used in forest inventory and forest characterization studies for decades already (Maltamo et al., 2007; Næsset et al., 2004). Alongside the estimation of regular forest inventory attributes, previous studies have provided evidence of the feasibility of utilizing ALS as an observation technique also for assessing forest structural complexity through different 3D voxel-based approaches such as CVPs (Coops et al., 2007; Harding et al., 2001; Hilker et al., 2010; Lefsky et al., 1999; Zhang et al., 2017). This method, as utilized also in this study, aims to assess forest structural complexity through the analysis of canopy layering structure, particularly from light availability perspective, which is a fundamental driver shaping forest structures (Franklin Jerry & Pelt Robert, 2004). It is a suitable methodology for structural complexity assessment when utilising sparse-density ALS data (Parker et al., 1995) that has become increasingly available in many countries through national campaigns (Moudrý et al., 2023). However, monitoring changes in forest structural complexity over time in different forest types has not been extensively studied, where this study aimed to contribute.

The experiments carried out in this study showed that the magnitude of changes in the canopy layering structure was observed to be higher in forest stands representing larger height variability, deciduous tree dominance, or higher species richness in general. The proportion of space occupied by vegetation increased while empty space below the canopy decreased over time. The space occupied by vegetation or empty space below the canopy generally increased with an increasing stand complexity. The findings obtained here, within boreal forest conditions, are generally in line with the existing knowledge of how CVPs characterize stand structural complexity through the canopy layering structure (Coops et al., 2007; Lefsky et al., 1999). It is known that canopy roughness is one of the forest structural complexity-related features connected to canopy dimensions, crown geometry, and branch distribution, and it is well characterized by the amount of open gap presence in CVP (Lefsky et al., 1999). In this study, the observed increases in the open gap proportions were not considered statistically significant especially in the deciduous dominated plots due to low number of samples. Modest changes in the other categories were most likely due to the characteristics of the forest stands, majority of which were representing more homogenous crown characteristics among tree individuals, resulting in a lower open gap proportion compared to mixed and structurally more diverse stands (Coops et al., 2007).

Regardless of forest type, the proportions of euphotic and oligophotic zones increased from 2012 to 2019 indicating that the upper canopy was getting more vegetated with larger and denser branches, resulting in a larger number of respective laser returns (Lim et al., 2003). In contrary to Zhang et al. (2017) where the oligophotic zone increased with respect to the photosynthetically active euphotic zone, we did not find similar trends in our experiment. Instead, both canopy layers, representing the space occupied by vegetation, increased approximately similarly, most probably due to the rather short monitoring period considering the life span of boreal trees (Maltamo et al., 2014).

Considering data sampling, it should be noted that we had a limited number of sample plots distributed over a relatively small study area (14 km^2). Although the plot locations had been selected to capture structural differences within the forest area, they cannot cover all the forest types and structural characteristics of the southern boreal forests conditions that they aim to represent. The stratification of sample plots by species richness and height variability categories was based on the observed variation between the sample plots. The stratification aimed to provide ecological grounds for assessing the observed changes in the canopy layering structure within different forest structural complexity categories. Thus, the used threshold values for Gini Coefficient and Shannon Equitability Index could not be applied as such outside the study area. In our experimental design we had only four deciduous dominant plots, making species type and richness related stratification unbalanced. Most likely, the low number of samples in that particular category caused the non-significance of the observed differences between canopy layering categories. However, we wanted to separate deciduous plots from conifer-dominated to preserve the ecological validity. Considering the timing of the data capture, the first ALS acquisitions took place in 2012, but conventional measurements were conducted in 2014. This inconsistency should not affect the results as the 2014 measurements were only used for sample plot stratification, and a two-year period in boreal conditions does not cause consequential difference in tree dimensions and species compositions.

The experimental design, the used instruments and the applied data processing settings can have directly influenced the obtained results. In this study both ALS data sets were collected during early-to-mid May with weather and phenological conditions as similar as practically possible. The instruments and point cloud acquisition parameters were selected to follow the data acquisition requirements of National Land Survey of Finland, thereby achieving as comparable point clouds as possible. On average, the point density was considered rather comparable, being 0.5 pts/m^2 in 2012 and 0.74–0.8 pts/m^2 in 2019. However, it is still possible that the slight differences between the datasets have affected their capacities of characterizing the structure of vegetation within the sample plots and thus possibly explain some of the observed differences during the monitoring period. These differences might be the most evident when regarding lower vegetation layers and structurally more diverse plots. Future research could provide insights into the feasibility of using CVPs with higher point density ALS data, e.g. around 5–10 pts/m^2, thereby giving more laser returns per unit area and a better comprehension about the inner canopy characteristics (euphotic and oligophotic light zones) as well as their development in time. CVPs are generated from voxels and thus the voxel size is an important variable because it directly influences the distribution of light class proportions (Zhang et al., 2017).

Overall, the findings obtained in this study show potential to improve and scale up the methodology to identify structurally and biologically diverse forest stands or hotspots in boreal forest conditions. Information extracted from ALS-derived CVPs could be a useful asset to support countrywide forest inventory planning or even give additional forest inventory perspective on structural complexity dynamics (Coops et al., 2007; Lefsky et al., 1999; Zhang et al., 2017).

Conclusion

This study was designed to enhance understanding on the feasibility of low-density ALS in monitoring the structural complexity of boreal forests. The experiments demonstrated the use of ALS-derived CVPs in characterizing changes in canopy layering structures, which implied changes in the structure of forest stands and their development towards greater or lesser complexity. The results showed that forest stands with higher degree of tree height variability and increased species richness featured higher magnitudes in the changes in canopy layering structure. The applied methodology enabled the assessment of how canopy properties – divided into volumetric units – change over time, to understand canopy layering dynamics. The experiments carried out in this study support the existing knowledge of the feasibility of low-density ALS in forest characterization, particularly providing contribution for assessing changes in the structural complexity of southern boreal forests through the observed changes in the canopy layering structure. This study showed the usefulness of open-source, multi-temporal, country-wide ALS data utilization for the assessment of forest structural complexity. The experiments provided evidence that the applied methodology has the potential to be implemented in a landscape-level mapping of forest structural characteristics.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

Availability of data - Data generated at a central, large-scale facility, available upon request.

Template for data availability statement - Raw data were generated at National Land Survey of Finland. Derived data supporting the findings of this study are available from the corresponding author Reinis Cimdins on request.

Policy - Basic, Share upon Request.

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