DETECTION OF SILVER BIRCH GROWTH DYNAMICS AND TIMING WITH DENSE SPATIO-TEMPORAL LIDAR TIME-SERIES

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ABSTRACT:

Silver birch (*Betula pendula Roth*) is a deciduous pioneer tree species with significant economic and ecological importance due to its rapid growth, high genetic variability and adaptability to diverse climates and environments. In this regard, understanding the factors that influence silver birch tree growth variability and its seasonal patterns has been a subject of research interests, which aim at effective forest management and ecological analyses. Tree size, competition, light availability, and topography has been considered significant factors affecting tree growth patterns. However, their relative contributions are not well understood. This is because, to study the interactions between neighbor trees and their competitive responses requires complex measurements. Accurately measuring tree attributes, such as 3D canopy shape and arrangement, is challenging but has been made possible through advancements in high-resolution 3D remote sensing, specifically laser scanning technology. This study shows the potential of high-spatial and temporal resolution LiDAR time-series from a permanent laser scanning setup to detect detailed structural changes and timing in individual tree canopies, focusing on assessment of the structural canopy growth characteristics of silver birch trees. We first investigate how silver birch trees respond to competition and neighboring species. Our results focusing on canopy height increment show that tree size, competition, neighboring species, and water availability affect the rate of vertical (height) growth of the studied silver birch trees. Further, we detect the timing in canopy vertical and horizontal growth using LiDAR time-series. Significant variations of up to one week were detected among trees, providing insights for future studies on growth dynamics of silver birch in coniferous-dominant forests.

1. INTRODUCTION

Tree canopy height and area growth rates can demonstrate considerable inter-variation among individual trees, even within the same species at same forest (Sánchez-Salguero et al., 2015). An understanding of the factors that affects growth variability between trees and annual seasonality can significantly contribute for forest management decisions and complex ecological analysis, including derived forest process such as carbon accumulation (Stephenson et al., 2014). A recognized factor that impacts tree growth and survival is resource competition (Sánchez-Salguero et al., 2015, Aakala et al., 2018, Chin et al., 2023).

According to Stoll and Weiner (2000), the positive and negative interactions between neighbor trees and their competitive responses occur at small spatial scales (e.g. 5m radius), requiring tree level analysis. Although tree size, competition, light availability, and topography have been widely discussed in the literature as main factors influencing tree growth patterns, the extent of their relative contributions are still not well understood (Zhang et al., 2017). The challenge arrives from the need of accurate measurements of standing tree, like accurate three-dimensional (3D) canopy shape and its arrangement with respecting to neighbouring trees.

Over the previous two decades, we have witnessed a notable evolution in our ability to accurately measure and analyse the structure and dynamics of trees with high-resolution 3D close range sensing data (Liang et al., 2022). Indeed, the real value of high-spatial resolution forest data acquisition is evidently demonstrated by the fact that full three-dimensional data enable to quantify features that have been impossible to measure before with other techniques (Lines et al., 2022). Laser scanning technology enables a unique 3D data collection and representation of trees structure as the laser beam has high penetrability in the canopy. When a tree grows and neighbourhood interactions take place among the canopies, georeferenced 3D LiDAR observations capture the structural changes, and they enable the understanding of tree growth dynamics. Moreover, it is possible to extract and estimate tree canopy parameters over time, such as horizontal (area) and vertical (height) canopy growth.

For instance, canopy height (Wang et al., 2019), leaf area (You et al., 2022), and biomass (Xu et al., 2021) have been previous estimated from aerial and terrestrial LiDAR point clouds. However, to estimate the uncertainties of forest attributes measurements are still non-trivial. According to Wang et al. (2019) and Jurjevic et al. (2020), the accuracy of tree height estimated based on ALS, UAV or TLS point clouds can range between few centimetres to meter-level of accuracy, depending on tree canopy shape, plot complexity, point cloud density, and data acquisition geometry. Tompalski et al. (2014) showed that bias in tree height estimates have a clear impact on further analyses and attribute estimates, such as an individual tree volume. The uncertainty impacting forest analysis becomes even more severe when repeated measurements are required, such as in estimating individual tree growth.

Permanent laser scanning (PLS) systems have been suggested as another potential alternative for tree growth estimations. PLS

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systems provide well registered LiDAR time-series as they monitor their respective forest scene from a fixed point of view. Yet, PLS systems measuring dense spatio-temporal time-series are still rare (Campos et al., 2021), and their use is especially underexplored in forest growth dynamic analyses. Here, we explore the potential of PLS time-series to monitor deciduous silver birch trees (*Betula pendula* Roth.) canopy growth dynamics and neighborhood characteristics. The vertical and horizontal growth characteristics were monitored using high temporal and spatial resolution LiDAR data time-series collected with the Finnish Geospatial Research Institute (FGI) PLS setup, FGI Lidar Phenology station (LiPhe) (Campos et al., 2021). We used LiPhe dataset collected over the 2020 growth season (April 2020 – April 2021) to detect and quantify silver birch growth dynamics and growth timing on weekly basis. Our aim is to investigate whether silver birch canopy follows some species-specific growth rules as effect to their local neighbourhood. We especially focus on the joint effect of competition and species identity on the growth rate of tree stands in terms of canopy height (Section 3.1) and its timing (Section 3.3).

2. MATERIALS AND METHODS

2.1 LiPhe LIDAR time-series

The FGI-Lidar Phenology station was designed to monitor daily and seasonal phenological changes in boreal tree species. The LiPhe data is capable of capturing changes with a temporal resolution as fine as one hour and a centimetric spatial resolution (1 cm between neighboring points within 100 m). Figure 1 illustrates the setup of LiPhe, comprising a Riegl VZ-2000i scanner mounted on a 35-meter tower above the forest canopy. The LiPhe station data have an intermediate data acquisition geometry between the ground and aerial perspective. The laser scanning system is tilted at a 60-degree angle downward, offering a unique point of view to measure the tree tops and outline changes of the below forest canopy within 200 m (Figure 1.b). LiPhe setup details can be found at Campos et al. (2021).

The LiDAR time-series used in this work is a subset of LiPhe dataset. In total, 91 time-points covering one year were selected between April 2020 and April 2021 with a bi-weekly temporal resolution (two scans per week). The scans were selected considering stable scanning conditions with no precipitation and prevailing wind speeds less than 3 m/s. Meteorological and atmospheric aerosol data are continuously monitored by the SMEAR station (SMEAR II, Junninen et al., 2009), facilitating scan selection based on weather conditions and study objectives.

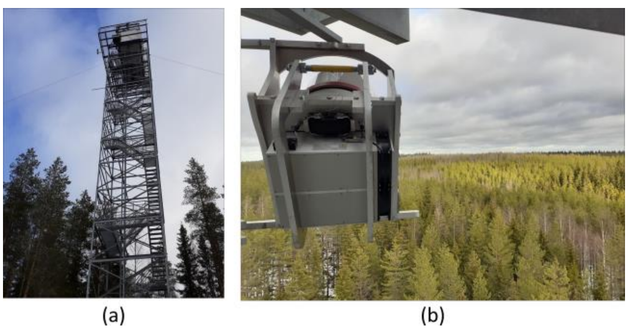

Figure 1. FGI-LiDAR phenology station: (a) the 35-m high measurement tower where LiPhe is installed. The laser scanner is securely mounted on a designed frame, located in the rear corner of the tower. Measurement computer is housed within a weatherproof container visible on top of the tower. (b) RIEGL VZ-2000i laser scanner mounted in the tower and top view over the test forest.

2.2 Silver birch dataset

Silver birch is a broadleaf pioneer tree species widely distributed in temperate climatic zones with significant economic and ecological importance, especially in northern Europe (Beck et al., 2016). In terms of economic value, silver birch is outstanding to its rapid growth and desirable stem characteristics, for instance, for furniture production (Stener et al., 2017, Dubois et al., 2020). From the ecological point of view, the high genetic variability and remarkable adaptability to diverse climates and environments make the silver birch a relevant species for studying adaptation mechanisms (Jansons et al., 2016, Oksanen, 2021, Possen et al., 2021). These recognized factors motivated recent studies on silver birch structural growth dynamics and management (Aun et al., 2021, Konôpka et al., 2021, Skovsgaard et al., 2021, Holmström et al., 2021, Matisons et al., 2022, Sitko et al., 2022, Martin-Blangy et al., 2023) and encouraged the choice of silver birch as main subject of the present study. It is important to highlight that different species have different responses to neighbouring factor, which can result in even more complex analysis. Therefore, to ensure the consistency of our findings, we focus in particular on silver birch species within the context of a coniferous-dominated boreal forest.

The silver birch trees under study are situated within the scanning area of LiPhe at the Hyytiälä forestry field station in southern Finland. The research is conducted in a coniferous-dominated boreal forest occupied by Scots pine (Pinus sylvestris L.), Norway spruce (Picea abies H. Karst) and silver birch, listed in order of predominance. The scanned forest is approximately 61 years old (2023) and it has an estimated stem density of 625 trees per hectare. Figure 2.a shows the distribution of silver birch trees (green) in the research area, in which the scanner position is represented with the orange triangle, silver birch trees positions are marked in green, while all the remaining trees mapped are presented by grey dots. Figure 2.b shows an example of an individual silver birch point cloud colorized by scanner-calibrated intensity values (LiDAR-Reflectance).

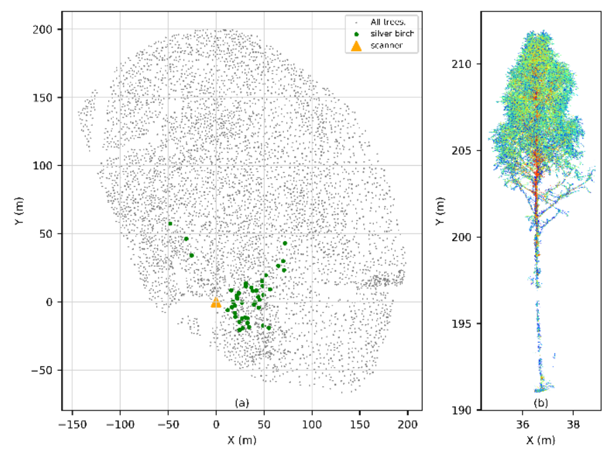

Figure 2. Dataset overview: (a) Research forest area (gray), highlighting silver birch (green dots) and LiPhe scanner position (orange triangle) and (b) example of silver birch tree point cloud.

A total of forty-three silver birch trees with full visibility (stem and canopy) to the LiPhe laser scanning system were selected for closer investigation (Figure 2). As mentioned, ninety-one (91) complete point clouds were processed, aiming to accurately monitor the studied silver birch trees over the period between

April 2020 and April 2021.The silver birch point clouds (time-series) were obtained using a comprehensive data processing framework which starts from LiPhe raw point clouds (full forest scene), resulting in georeferenced tree level point clouds (ETRS89/TM35FIN coordinate system). The data processing steps involve point cloud registration, georeferencing, stem detection, coarse-to-fine point cloud segmentation, data resampling by voxelization (5 cm voxel), and estimation of tree parameters (such as tree canopy height and area over time). The entire pipeline was implemented using Python programming language.

Despite of the small number of silver birch trees to be analysed, data selection was performed considering a representative sample of the variability of both local conditions and tree density featured by their neighborhoods in the research area (Figure 3). A neighbouring tree was defined as those within a 5-meter radius cylinder centred at the study tree's stem. Figure 3 shows in panel (a) the number of silver birch trees according to the neighboring species combination, while, panel (b) summarize the number of trees by number of neighbors within 5-m radius ranging from zero to sixteen.

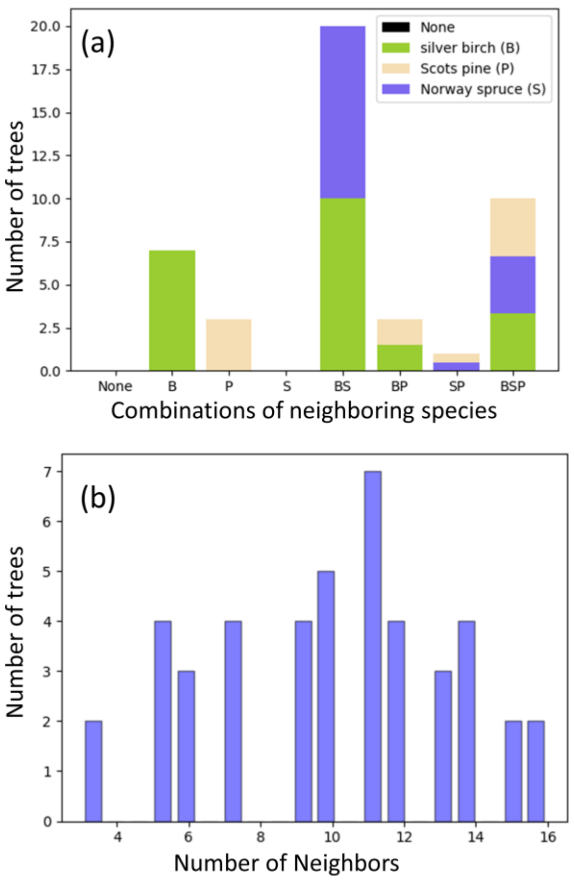

Figure 3. Summary of silver birch trees neighbourhood variability in terms of neighbouring species (a) and density of neighbours (b), ranging from zero to sixteen neighbours.

2.3 Tree parameter estimation

Aiming to demonstrate the potential of PLS time-series data in detecting detailed structural changes, we have successfully extracted silver birch canopy parameters and neighborhood information from LiPhe dataset. The main parameters extracted from the LiDAR time-series for each of the forty-three silver birch trees were the tree initial height ($H_{April20}$) and area ($A_{April20}$) (April/2020), absolute and relative growth in height (ΔH) and in area (ΔA), number of neighbours (NN) and neighbouring species (Figure 3), competitive index (CI) and topographic wetness index (TWI). Table 1 summarizes the methods and equations used in estimating these tree parameters.

Two distance-dependent competitive indexes (CI6 and CI8) were used to estimate the tree competition based on tree height (Hj), neighbouring trees height (Hi), and the distance between them (Lij). The competition indices applied in the study are well-established indices derived from Rouvinen and Kuuluvainen (1997). The TWI was calculated as a function of total catchment area (TCA), flow width (FW) and slope (S) (Kopecký et al., 2021), which was computed using a LiDAR-DTM (digital terrain model) of LiPhe research area and SAGA-GIS (System for Automated Geoscientific Analyses).

Parameters	Method
$H_{April20}$	99.95th height percentile
ΔH_{abs}	$H_{April21} - H_{April20}$
ΔH	$(H_{April21} - H_{April20})/H_{April20}$
$A_{April20}$	2D (x, y) Alphashape; Vauhkonen et al. (2010)
ΔA_{abs}	$A_{April21} - A_{April20}$
ΔA	$(A_{April21} - A_{April20})/A_{April20}$
CI6	$\sum_{j=1}^{n} \tan^{-1}[(H_j - 0.8H_i)/L_{ij}],\ H_j > 0.8H_i$
CI8	$\sum_{j=1}^{n} \tan^{-1}[(H_j - H_i)/L_{ij}],\ H_j > H_i$
TWI	$\ln(TCA/FW)/\tan(s)$; Kopecký et al. (2021)

Table 1. Summary of methods applied for the estimation of tree parameters based on LiDAR data time-series.

Figure 4 shows examples of height and area growth monitoring of an individual silver birch trees by LiPhe. The outlines (*leaf-off*) of the tree canopy at Apr. 2020, Oct. 2020 and Apr. 2021 are presented in Figure 4 (a), while the area growth and direction are quantified in Figure 4 (b). The example case shows a canopy growth towards South and Southwest direction with maximum magnitude around 0.4 m. Figure 4(c) illustrates the variations of the median scanner-calibrated intensity values, referred to as LiDAR-Reflectance, across various canopy heights over the year 2020. The scanner-calibrated intensity values are defined by Riegl (RIEGL Measurement Systems, 2020) as a property representing the proportion of incident optical power reflected by a specific target at a wavelength of 1,550 nm, measured in decibels (dB).The individual tree point cloud was divided in four height segments (bottom, lower-mid, upper-mid and top) defined between the 0-50th, 50-70th, 70-90th and 90-100th height percentiles of the birch tree canopy at the first time point (April/2020). By monitoring the LiDAR-Reflectance response over the time-series, it is possible to detect and time the signal of the sprouting and growing of new leaves in spring 2020 and the falling of the leaves in autumn. The highest magnitude reflectance variations were detected in the top layer of the tree, where most of the new growth happens. Figure 4 (d) illustrates the height growth timing with the growth starting in May 2020 and ending after the beginning of the fall (Sep 2020), with the total magnitude of 40 cm.

The relationship between neighbourhood (competition and species) and tree relative growth in height (Section 3.1) and area (Section 3.2), as well as the detection of the timing of the growth (Section 3.3) were investigated based on the parameters estimated from the LiPhe-LiDAR time-series (Table 1). We discuss the results against previous conclusions in existing literature based on traditional forest inventory methods (*in situ* survey).

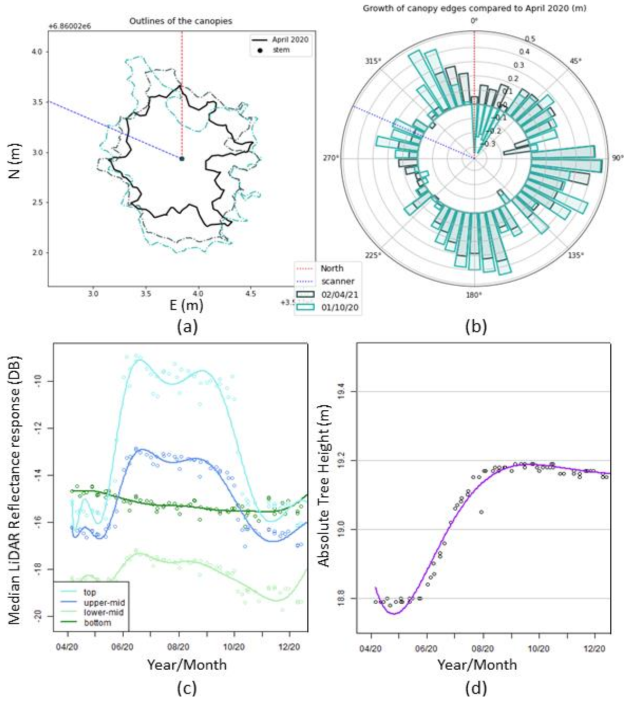

Figure 4. Example of silver birch growth dynamics over 2020 growth season: (a) outlines of the tree canopy at Apr. 2020 (black), Oct. 2020 (cyan) and Apr. 2021 (gray); (b) Azimuthal canopy growth direction; (c) Median LiDAR-Reflectance response at 0-50th, 50-70th, 70-90th and 90-100th height percentiles and (d) silver birch height estimated overtime.

3. RESULTS AND DISCUSSION

3.1 Silver birch height growth and neighbourhood effects.

Table 2 present the minimum, maximum and average height ($\mu H_{April20}$) and canopy area ($\mu A_{April20}$) of the forty-three silver birch trees in April 2020. As well as the standard deviation of the canopy height and area between the trees ($\sigma H_{April20}$, $\sigma A_{April20}$). The development of the silver birch canopy is summarized by the same statistics for absolute and relative vertical (ΔH_{abs}, ΔH) and horizontal growth (ΔA_{abs}, ΔA) of the studies trees. Evidently, a distinct variability in both height and canopy area growth rates can be observed among the silver birch trees in the research area. The absolute height growth rates vary between 11 cm and 48 cm within the dataset, while the absolute canopy area growth ranges from 1.55 m^2 and 17 m^2. Those variability shows that silver birch trees have different growth patterns even when they are living under similar general forest stand conditions. Thus, the detection of asymmetry growth patterns highlights the important role of driving factors at micro scales, particularly the interactions among neighbouring trees within a microenvironment at local. Neglecting these relations can lead to a misunderstanding of the interaction between individual trees and the entire community, as also discussed by Stoll and Weiner (2000).

An indication that competition and water availability stimulate vertical growth was detected. Our analysis shows that silver birch relative height growth (ΔH) has existing correlations with tree height (-0.47), CI6 (0.3), CI8 (0.43) and TWI (0.38). Figure 5 shows the correlation matrix between those variables with ΔH. We further investigated the effects of tree initial height, CI8 and TWI on the relative height growth of silver birch trees using linear mixed-effect regression analysis (Bates et al., 2015). A small correlation between competition and the number of birches (NB), pines (NP) and spruces (NS) was detected. Therefore, the influence of the dominant coniferous or deciduous neighborhood in ΔH was also assessed. Table 3 show the summary of significant explanatory variable defined by the linear mixed effect models. An explanatory variable was considered significant if its p-value (p) was less than 0.05.

Tree param.	$H_{April20}$ (m)	ΔH_{abs} (m)	ΔH (m)	$A_{April20}$ (m^2)	ΔA_{abs} (m^2)	ΔA (m^2)
Min.	11.05	0.11	0.006	1.55	0	0
Max.	25.45	0.48	0.04	17.5	2.42	0.32
μ	18.28	0.26	0.01	6.49	0.50	0.08
σ	2.97	0.09	0.01	3.39	0.48	0.06

Table 2. Minimum, maximum, average and standard deviation of the estimated height and area (April 2020) and absolute and relative height and area growth based on LiDAR data time-series between April 2020 and April 2021.

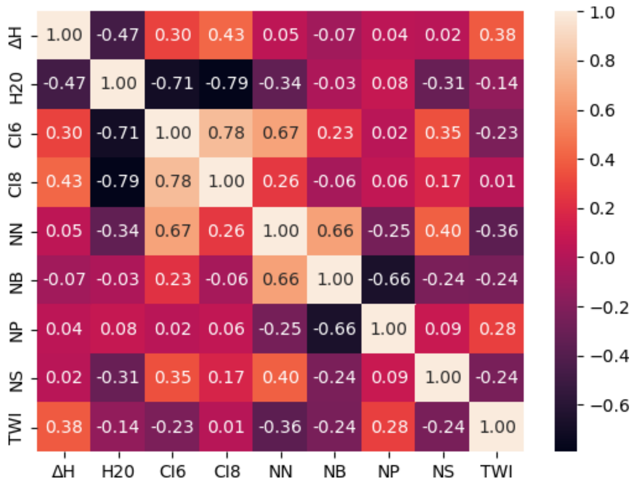

Figure 5. Correlation matrix containing the correlation coefficients between relative growth in height (ΔH) and the possible explanatory variables, tree height at April 2020 (H20), competitive index (CI6 and CI8), topographic wetness index (TWI), number of neighbours (NN) and number of silver birch (NB), Scots pine (NP) and Norway spruce (NS) as neighbours.

By the results of the linear mixed effect models, we found indications that initial tree height (tree size), competition and water availability expressed by TWI have the most significant impact on relative growth in height.

Predictors	Estimates	CI	p
$H_{April20}$	-0.00	-0.00 - 0.00	0.002
CI8	0.00	0.00 - 0.00	<0.001
TWI	0.01	-0.00 - 0.01	0.005
$N_{DECIDUOUS}$	-0.02	-0.04 - 0.00	0.041
$N_{CONIFEROUS}$	0.02	0.00 - 0.04	0.041

Table 3. Significant explanatory variable defined by the linear mixed effect models results.

The growth of silver birch trees in the studied dataset is negatively influenced by the initial tree size ($H_{April20}$), with smaller silver birch trees demonstrating more pronounced relative height growth during the 2020 growth season. While some authors have found a positive contribution of initial tree size to ΔH in silver birch, especially in earlier growth stages, (Jõgiste et al., 2003, Kund et al., 2010), it is important to consider that the relationship between growth rate and tree size is

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multifaceted, particularly in mixed-species forests (Río et al 2014, de-Dios-García et al 2015, Zhang et al., 2017, Martin-Blangy et al., 2023). Previous studies discussed that tree height growth rates are dependent on age and hydraulic mechanisms (Koch et al., 2004).

TWI exerts a positive influence on the relative growth in height (ΔH). Higher water availability stimulates greater relative growth in height of the silver birch trees in the research area. Despite of silver birch adaptability to different soil moisture conditions, previous works also highlight the positive effect of water availability on silver birch relative height and stem diameter growth rates (Possen et al., 2011, Jansons et al., 2016). In the same direction, Mohamedou et al. (2017) show the potential of TWI derived from LiDAR data to improve silver birch growth predictions, expressed by increment in diameter at breast height.

Competition (CI6 and CI8) affects positively the relative growth in height (ΔH) of the silver birch trees in the research area. This result aligns with the conclusions presented by Kaitaniemi and Lintunen (2010), who also observed an effect of the interaction between competition and neighbor identity in silver birch height growth. Their study concluded that increased competition, as expressed by CI6, accelerated height growth in silver birch. Konôpka et al. (2020) observed that under severe competition, silver birch trees tend to allocate more resources towards height growth rather than diameter growth. These previous works highlighted as well, similar silver birch growth strategy, in which diameter at breast height, basal area and biomass growth was negatively affected by competition from neighboring trees but positively affect height increment (Kaitaniemi and Lintunen, 2010, Konôpka et al., 2020).

Considering the neighbourhood composition, our findings suggest that an increased proportion of birch trees in a 5-m radius neighbourhood leads to a reduction in relative growth for height. Conversely, a higher percentage of coniferous trees in the neighbourhood composition corresponds to larger ΔH. Negative impact of silver birch neighbourhood was also suggested by previous works. For instance, Hynynen et al. (2011) concluded that height growth of birch species was considerably greater in pine-dominated than in birch-dominated stands.

3.2 Silver birch area growth and neighbourhood effects.

Similar to height growth rates, we investigated the correlations between tree height ($H_{April20}$), canopy area ($A_{April20}$), competition (CI6, CI8), and TWI with relative area growth of silver birch trees (ΔA). Figure 6 shows the correlation matrix between those variables with ΔA. Silver birch initial area ($A_{April20}$) has significant correlations and inverse correlations with tree height (0.81), CI6 (-0.62), CI8 (-0.58), number of neighbours (-0.31) and TWI (-0.31), which may initially indicate that those variables play a role on shaping canopy architecture (Kaitaniemi and Lintunen, 2010, Martin-Blangy et al., 2023). No significant correlations were found between tree size, competition and TWI with ΔA.

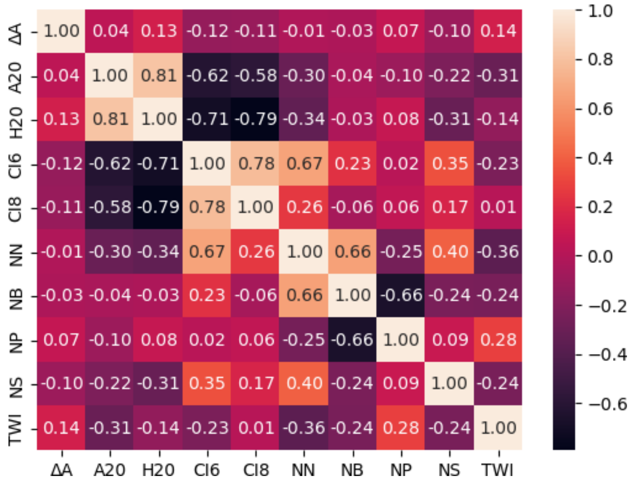

Figure 6. Correlation matrix containing the correlation coefficients between relative growth in area (ΔA) and the possible explanatory variables, tree area at April 2020 (A20), competitive index (CI6 and CI8), topographic wetness index (TWI), number of neighbours (NN) and number of silver birch (NB), Scots pine (NP) and Norway spruce (NS) as neighbours.

Less significant results were found regarding silver birch area growth effect by linear mixed-effect model results. Preliminary assessment indication that TWI (p = 0.018) and tree size (p = 0.041), expressed by the relationship between $H_{April20}$ x $A_{April20}$, positively influences area growth of the studied silver birch trees. Previous works have suggested that light and water availability (Martin-Blangy, 2023, Forrester and Bauhus, 2016), competition (Lintunen and Kaitaniemi, 2010) and tree-size (Guillemot et al., 2020) can be explanatory variables of tree canopy growth and architecture changes. However, they also highlight that due to the intricate relationship between canopy architecture, local environmental conditions, and tree growth, it becomes challenging to separate the effects. For instance, Forrester and Bauhus (2016), concluded that mixture effects of light interception in canopy dimensions would become stronger when water is not a limiting resource.

Although no significant effect of competition on relative area growth was observed in this study, Lintunen and Kaitaniemi (2010) have demonstrated that in silver birch trees, canopy structural variables (branch-level) are influenced by the interactive effects of neighbour identity and competition. These results and the high level of mixture effects complexity suggests that more complete analysis need to be performed to better understand the structural canopy growth characteristics of silver birch trees detected by LiDAR time-series.

3.3 Silver birch canopy height and area growth timing

By considering the height, canopy area, and LiDAR-Reflectance changes over time derived from the LiDAR time-series (Figure 4), we could identify the timing of silver birch growth during the 2020 season. Figure 7 shows an example of the tree height variation from April to December 2020. The start of the growth in height (magenta asterisk) and the point of height growth stabilization (green asterisk) were detected using a signal processing framework designed to identify breakpoints in the time-series (Truong, Oudre, and Vayatis, 2020). Table 4 presents the minimum, maximum and median day of the year (doy/2020) associated with the timing of height, area (canopy 2D alphashape) and leaves initial growth (LiDAR-Reflectance) of the studied silver birch trees, as well as the total difference and standard deviation in days between the trees.

Param.	Min (doy)	Max (doy)	Δ (days)	$\tilde{x}$ (doy)	σ (days)
Height.	125	167	42	137	9.5
Area	125	137	12	125	4.3
Leaves	137	149	12	139	2.4

Table 4. Minimum (Min), maximum (Max), maximum difference (Δ), median ($\tilde{x}$) and standard deviation (σ) of the estimated timing (day of the year) of canopy height, area and leaves initial 2020-growth based on LiDAR data time-series.

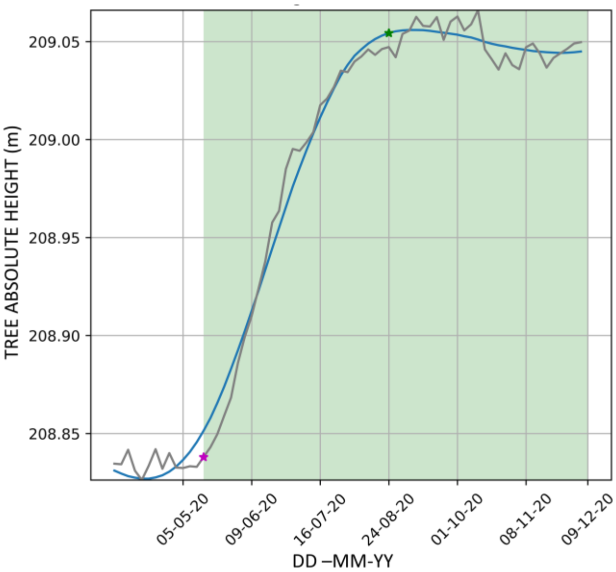

Figure 7. Example of silver birch height increment overtime over 2020 growth season and timing detection of the start of growth (magenta asterisk), in which the curve in grey show the estimated height values by 99.95th height percentile and in blue the smoothed curve by Savitzky–Golay based filter.

Based on our findings, the 2020 growth season in the studied silver birch trees occurs between earlier May and late August. The detection of both height and area growth among the studied trees begins on May 4th (doy 125). Certain trees exhibited earlier and delayed height growth in relation to the median (May 16th). Most part of trees start the height growth around May 16th and May 18th (doy 137 – 139). The variability in horizontal growth initiation among the trees was estimated to be around two weeks. In contrast, vertical growth differences range up to a month, with an average deviation of approximately 10 days between individual trees. The silver birch trees that experience late initial height growth (doy > 150) are mostly suppressed trees with more than 10 neighbours. However, further investigations are necessary to explore the drivers influencing the variability in growth height and area timing.

Interestingly, there was an estimated difference of around 10 days when comparing the initiation of area growth detected by 2D Alphashape method and detected by changes in LiDAR-Reflectance. This discrepancy can be attributed to the sensitivity of LiDAR-Reflectance response to leaf-related changes, indicating the growth of leaves. On the other hand, the 2D Alphashape outline can be sensitive to the branch angles, which are direct influence by the burden of snow, water content and leave density. These results highlight the complexity of canopy area change detection. Further studies aiming for precise canopy area estimation should consider branch angles calibration methodologies. These distinct indicators from LiDAR time-series can provide different insights into the aspects and stages of tree canopy growth during the spring season.

The results show in Table 3 can be discussed according to the main trigger of bud break and tree growth in spring, temperature and photoperiodic (Walde et al., 2022). According to Ruosteenoja et al. (2011), the growing season in the studied region begins once the mean daily temperature exceeds 5 degrees Celsius. This climatic condition is typically observed between April and early May in southern Finland, approximately six weeks after the March equinox. Prior to spring growth progression, tree species native to temperate climates, such as silver birch, require a chilling period that inhibits budburst during the warmer mid-winter period. This chilling requirement is characterized by a specific time frame in which temperatures range between 0°C and 5°C, or even higher, depending on the species (Harrington et al., 2010).

To compare the temperature at Hyytiälä research area in the detected days to the requirements mentioned above (Table 4), we estimated the cumulative growing degree-days (GDDs) for the year 2020 and assessed the length of day. GDD is a well know indicator of plant growth development which consider the accumulated heat based on the average daily temperatures compared against a base temperature. Typically, the base temperature for most plant species is around 5°C, which was applied in this study. If the average temperature was below the base temperature, the accumulative GDD value was considered zero. GDDs was estimated considering January 01 as the starting day. Temperature (above canopy – 33.6 m) and length of the day were obtained from SMEAR II.

According to our calculations the 2020 accumulated GDD reached values greater than 5 degrees at April 21 (at 33.6 m – above canopy) with a length of the day of 15 hours and 24 minutes. We detect the first signal of height and area growth on May 4 (doy 125), when the accumulated GDD above canopy was higher than 10 degrees (12.21°C) with a length of the day of 16 hours and 34 minutes. Therefore, the detected days are consistent with the conditions that trigger the growth described in previous works (Harrington et al., 2010, Ruosteenoja et al., 2011, Walde et al., 2022).

4. CONCLUSIONS

This study arrived in the follow perspectives and conclusions:

- LiDAR time-series analysis proved to be a reliable tool for accurately detecting the timing of growth and quantifying it when a temporal resolution adequate to detect the spring events is considered (< 1 week).

- Permanent laser scanner setups provide a unique approach for generating long-term LiDAR time-series. LiPhe dataset enables consistency analysis of forest growth dynamics supported by previous works conclusions based on traditional forest inventory surveys. The findings highlighted the importance of conducting individual tree analysis, especially regarding the asymmetry growth patterns detected at micro scales.

- In addition, the directionality of the growth through the gaps directions shows the potential of PLS time-series to support the understanding of how trees fill the canopy space occupation, which has recognized relevance for forest management.

- Future works addressing PLS occlusion limitation, aiming to increase the sample size of study trees are need. The LiPhe oblique perspective can suffer with occlusion caused by vegetation obstructions, especially during the growth season. Increasing the number of study trees would enhance the representativeness of the silver birch growth dynamic conclusions.

- Regarding growth dynamics, silver birch vertical growth (canopy height) was affected by tree size, competition, neighboring species, and water availability expressed by TWI.

- Silver birch horizontal growth (area) was affected by initial tree size in April 2020 and TWI. Although the results were inconclusive, the LiDAR time-series data demonstrated the potential to extract additional information that may contribute to explaining the observed variations in tree growth area. These findings are specific to the silver birch species and the particular area of study.

- Future works exploring the factor that drive the variability in initial canopy height and area growth timing detected by LiDAR time-series are recommended.

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