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# Influence of phenology on waveform features in deciduous and coniferous trees in airborne LiDAR



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#### ABSTRACT

Information on forest structure is vital for sustainable forest management. Currently, airborne LiDAR remote sensing has been well established as an effective tool to characterize the structure of canopies and forest inventory variables. Radiometry and geometry are highly intertwined in LiDAR remote sensing of forest vegetation and phenology influences the geometric-optical properties of deciduous and evergreen trees causing seasonal variation in LiDAR observations. This variation may be considered as a nuisance or exploited in for example tree species identification. Airborne LiDAR data are also influenced by sensor functioning, acquisition settings, scan geometry and the atmosphere. Reliable estimation of subtle phenological effects calls for data in which the impact of the external factors is minimal. We experimented with such data and explored LIDAR waveforms (WFs) in boreal trees in winter, early summer and late summer. Our objectives were to i) assess the match of the multitemporal LiDAR data for observing true changes in vegetation; ii) quantify the influence of phenology in deciduous and evergreen trees; iii) study the effect of varying scan zenith angle (SZA) and canopy age on WF features in different phenostates; iv) assess the temporal feature correlation in individual living and dead standing trees. A WF-recording pulsed LiDAR sensor unit operating at the wavelength of 1550 nm was used in repeated acquisitions. WF attributes such as energy, peak amplitude and echo width were derived for each pulse and were localized vertically to crown, understory and ground components. Silver and downy birch, black alder, European aspen, Siberian larch, Scots pine, Norway spruce and dead standing spruce formed our strata. Results showed that phenology caused more variation in WF features of deciduous trees compared to evergreen conifers. Deciduous trees displayed substantial between-species variation that was linked with differences in branching pattern, leaf orientation and bark reflectance. Pine displayed a possible winter-early summer anomaly in canopy backscattering that may be linked with changes in foliage clumping or with the role of stamens in early summer trees. Trees displayed positive temporal correlation in WF features and correlations were the strongest in evergreen and deciduous conifers and decreased with time. SZA had minor influence on WF features whereas age exercised a strong effect on many features with parallel variation between species and phenostates. Structural changes following death, i.e. 'aging' changed the geometric WF features of dead standing trees. Our results provide new insights for enhancing tree species identification by using WF LiDAR and for LiDAR time-series analysis of vegetation.

# 1. Introduction

Airborne pulsed LiDAR was quickly adopted in forest inventories following pioneering research (Hyyppä and Inkinen, 1999; Næsset, 2002). LiDAR is an efficient tool for assessing canopy density and height, due to its unique capability of directly measuring the three-dimensional structure of the canopies. Despite ample research, imprecision of species identification and characterization of suppressed trees constitute topics

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that call for improvement (Fassnacht et al., 2016; Venier et al., 2019). In addition, the need for field reference increases costs and has motivated attempts to improve the transferability of interpretation models between inventory areas (Toivonen et al., 2021). Understanding the factors influencing LiDAR observations is central for the success of such attempts. Seasonal variation is an important factor to consider.

Previous studies have mainly focused on the effects of phenology when using geometric features calculated from LiDAR point clouds (Kim et al., 2009; Simonson et al., 2018), but the phenological effects on LiDAR intensity and waveform (WF) features have received little attention (Salas, 2021). This is not an optimal situation, because the intensity and WF features have been shown beneficial for, e.g., tree species identification (Reitberger et al., 2008; Hollaus et al., 2009; Korpela et al., 2010a; Hovi et al., 2016). Understanding the phenological variations and the factors controlling them can help to determine optimal acquisition periods and to develop more general interpretation models for intensity and WF data. Quantifying the phenological effects on LiDAR WF signals can also help to understand the causes and consequences of phenological effects in point cloud data, because the radiometry and geometry in LiDAR data are intertwined.

Forest vegetation forms 'soft' targets in which the backscatter crosssection profile is deeper compared to 'hard targets' such as cables or road surfaces (Wagner, 2010; Hancock et al., 2015). Targets' directional reflectance properties (Li et al., 2013), size and orientation all influence the backscatter cross-section profile (incl. Multiple scattering, Hovi and Korpela, 2013). The return signal entering the aperture is a convolution of the transmitted pulse with the backscatter profile of the illuminated targets. The shape of the recorded signal is further transformed by the receiver (Wagner et al., 2006; Wagner, 2010). Backscatter profile changes with the wavelength, angle of incidence (directionality of gaps and scattering elements) and footprint diameter (gap size distribution, Korpela, 2017). Shape of the transmitted pulse influences the pulsetarget convolution and if the transmitted pulse is short, the return signal has more details. Spherical losses influence the signal enormously, and the impact depends on the target geometry, which makes range-normalization an ill-posed task. It is possible to compensate spherical losses only if the targets' geometry is identified first (Wagner, 2010). Transmitted power influences linearly the received power, and high-quality transmitters display minimal between-pulse variation. In addition to range-induced losses, 2-way atmospheric attenuation causes signal losses. Radiometry and geometry are highly intertwined in LiDAR and for example, a small dry target may trigger the receiver, but remains undetected if the same target is wet or if the pulse intersects the target off the center of the pulse, where the irradiance is at maximum (Korpela et al., 2013).

In using multitemporal LiDAR, a failure to address the many external factors that influence LiDAR backscattering may result in a false observation regarding vegetation changes. In this study, we use a waveform-(WF-)-recording LiDAR to detect changes in trees that are caused by phenology. Phenology can be considered a nuisance or it can for example be used to enhance tree species identification (Sayn-Wittgenstein, 1978; Kim et al., 2009). The effects of phenology have not been extensively explored in WF data (Salas, 2021). WFs disclose the measurement process in more detail compared to discrete-return (DR) data, which is beneficial in vegetation (Reitberger et al., 2008; Mallet and Bretar, 2009; Heinzel and Koch, 2011; Roncat et al., 2014; Hancock et al., 2015; Hovi et al., 2016; Anderson et al., 2016; Korpela, 2017; Korpela et al., 2020). Practical forest inventories often combine LiDAR datasets that are collected at different times of the year. Hence phenological variation is often present in the data. In boreal forests of Finland, deciduous trees are without leaves for nearly seven months and the development of new leaves in the early summer varies between species and is also influenced by micrometeorology. The needle mass in evergreen conifers increases during the summer. In pine, even the distribution of needle orientation shows seasonal variation, because the needle angle varies with the age of the needles (Stenberg et al., 1994). Conifers

bloom in the spring and drop the oldest needle cohorts in early autumn. Cones may change the reflectance properties of crowns and their weight may affect the orientation of the wintering branches. Even the water content of branches and leaves was shown to influence branch orientation (Junttila et al., 2022).

In Finland, Hovi et al. (2016) investigated multitemporal 1064-nm WF data acquired with a Leica ALS60 sensor. The acquisitions were done in June-August. They explored within-species WF feature variance. A species-dataset interaction term explained up to 10% of the variance and a part of this was deemed to be caused by sensor and acquisition settings that varied slightly from year to year. Hovi et al. (2016) however highlight a phenological effect between two campaigns, which differed less in acquisition settings. Namely, relative to spruce (Picea abies H. Karst), the return energy of pine (Pinus sylvestris L.) increased 3-4% during the summer and the authors linked this with the 25–30-% increase in needle mass of pine. In deciduous trees the absence of leaves impacts pulse penetration and hence the point height distributions, and, as shown by Davison et al. (2020) using discrete-return (DR) data, both leaf-on and leaf-off data have their benefits in describing structural diversity of forests in the UK. Combination of leafoff and leaf-on DR data, although more expensive for the end-users, was shown to enhance species identification of broadleaved birch in seedling stands in Finland (Imangholiloo et al., 2020). And, studies conducted in forests dominated by evergreen needleleaf conifers in Norway, Finland and Canada have shown that LiDAR captured in leaf-off conditions performs nearly as accurately as leaf-on data in area-based estimation of stand density, biomass and height traits (Næsset, 2005; Villikka et al., 2012; White et al., 2015).

In this study we examined the effects of phenology on WF LiDAR data acquired at the wavelength of 1550 nm. The data were obtained from three repeated (winter, early summer, late summer) acquisitions over a boreal forest site in Finland. We aimed at minimizing all external factors that influence LiDAR observations to obtain accurate estimates of phenological effects on LiDAR WFs in trees. The experiment included observations of pine, spruce, silver birch (*Betula pendula* Roth), downy birch (*Betula pubescens* Ehrh.), European aspen (*Populus tremula* L.), black alder (*Alnus glutinosa* (L.) Gaertn.), Siberian larch (*Larix sibirica* Ledeb.) and dead standing spruce. Our general aim was to increase understanding of LiDAR observations for applications in forest monitoring and tree species classification. Our specific research questions (RQs) were:

RQ1. What was the accuracy of the repeated LiDAR data for finding true signal changes caused by vegetation phenology?

RQ2. What is the level of variation in winter, early summer and late summer WFs in deciduous and evergreen species?

RQ3. What are the signal changes in the repeated LiDAR acquisitions in dead trees that are not influenced by phenology?

RQ4. Which WF features correlate over time and do the correlation patterns vary with species or display phenological signals?

RQ5. Are the WF features influenced by scan zenith angle or tree age and do the dependencies vary with phenology?

#### 2. Material and methods

# 2.1. Outline of the experiments

Fig. 1 shows the data and processing steps. There were three LiDAR acquisitions (11/2011, 5/2013, 8/2015) separated by 18 and 27 months. They are referred to as 'winter', 'early summer' and 'late summer' and were captured in this order. Geometric and radiometric match of the datasets was tested systematically in non-tree targets (RQ1). Data were analyzed at stand and tree levels The plot-level analyses were conducted on circular plots in pine, spruce and birch stands. Tree-level analyses covered more species. WFs were assigned to individual trees using 3D pulse tracing in crown envelope models that were fitted to each tree. Pulse tracing enabled a partitioning of the return WF between



Fig. 1. Flowchart of the study.

crown, understory and ground segments. Several WF attributes describing the shape and return energy were computed for each pulse. Many of the attributes were from Hovi et al. (2016). WF features of trees and plots were distribution metrics of pulse attributes. Each plot and tree had winter, early summer and late summer features, which were compared between acquisitions (RQ2, RQ3) and analyzed for correlations (RQ4, RQ5).

#### 2.2. Hyytiälä study area and research infrastructure

The experimented was conducted in Hyytiälä, Finland (61.85°N, 24.29°E). The forests are dominated by pine and spruce. Birch (silver and downy birch) occurs mainly as a mixed species. These are the main tree species in Finland. Other species were aspen, alder and larch. The age structure of Hyytiälä forests is shaped by a clear-cut regime that began in 1950 and has favored pine and spruce. Birch was planted only after 1972. Deciduous trees are in full leaf from late May until mid-September (larch until mid-October). New needles develop in June. Pine drops the oldest needles in early September and 2-3 needle cohorts overwinter. Spruce has 6-9 needle cohorts. Depending on the site quality, pine and spruce attain the heights of 21-33 m at the age of 100 years, while the growth of birch is slightly faster. Dominant trees are not harvested in intermediate fellings so that tree height correlates strongly with stand age. Elevation varies moderately (140-195 m above sea level). There have been systematic aerial imaging and laser scanning campaigns since 1985 and 2004, respectively. The oldest aerial images are from 1946. All images have been oriented (see Korpela, 2006) using bundle block adjustment to sub-pixel accuracy. We used a LiDAR elevation model in 1-m resolution, which has displayed an RMSaccuracy of circa 20 cm. Historic images were used for the estimation of stand age and high-resolution images (10-20 cm, 2004-2015) were used for assessing the time of death of individual trees. We used meteorological and sun-photometer observations of the SMEAR II station to evaluate between-campaign differences of atmospheric losses of LiDAR signals.

# 2.3. Airborne LiDAR and concurrently captured image data

The same Riegl LMS-Q680i sensor unit was used in all campaigns (Table 1). Sensor settings, trajectories and flying speed were kept unchanged. The dates were Nov/15/2011 (09:54–10:35 UTC), May/28/2013 (10:45–11:30) and Aug/18/2015 (09:03–09:50). An RGB camera was operated simultaneously. Dry weather had prevailed in the preceding days in all campaigns. Weather in summer acquisitions was comparable (humidity 50% and 40%; pressure 1000 and 1010 hpA; visibility 40 and 48 km). The winter acquisition in 2011 took place also under clear sky conditions. Air temperature at the flux tower was  $-3 \,^{\circ}$ C at sunrise (06:35 UTC) and rose from  $-1.2 \,^{\circ}$ C to  $+0.2 \,^{\circ}$ C during the scanning (solar elevation 9.6°, visibility 50 km). Sun-photometer was not operational in 2011, but in 2013 and 2015, the 1640-nm aerosol optical density values were very low (0.022 and 0.011) as were the estimates of precipitable atmospheric water (1.26 cm and 1.09 cm).

LMS-Q680i saves a WF sample of the transmitted pulse and the received WF consisted of 1–3 sequences with 80, 160, 240 or 320 amplitude values. There can be pauses between sequences, if the back-scattering dims between the canopy and ground (Fig. 12). A 10–12-ns long buffer starts the first sequence, and each new sequence after a

Table 1			
Campaign	and	sensor	settings

Parameter	Value
Platform	Helicopter
Flying speed, m s <sup>-1</sup>	40
Nominal flying height, m	750
Sensor scan angle, degrees	+/- 30
Number of strips	8+1
Strip overlap, %	75
Wavelength, nm	1550
Beam divergence (86.4%)	0.5 mrad
Footprint diameter, cm	35–45
Pulse length (FWHM), ns	4.5
Pulse frequency, kHz	240
WF sampling rate, ns	1
WF amplitude bit depth	16
Camera	Hasselblad H4D
Pixel size of RGB images, cm	10

pause. We considered the amplitude values as measurements of instantaneous received power. The receiver has two signal channels, which differ 6 dB in gain. The combination expands the dynamic range of the sensor. RiAnalyze (RiA) was used for processing the WFs into DR data. RiA applied a factory calibration to the DR intensity observations. DR points were essential for strip adjustment and for computing the 3D pulse vectors. Strip overlap was 75% and it means that a ground point was 'viewed' by four strips. Although the trajectories matched well (<30 m), the pulse geometries had minor differences between campaigns. The scan zenith angle (SZA) distributions of the same ground points did not always match especially if an 'oblique strip' was missing in one campaign due to sensor sway and/or trajectory offset. Only the joint strips were accepted for trees to have the SZA distributions match.

Phenology was observed during the campaigns. There was frost on many open surfaces in the winter data (2011), while canopies and sunlit surfaces had none. In early summer data (2013), birch was in full leaf, but aspen leaves were not entirely developed in some clones. New shoots in pine (with stamens) and spruce had started to grow the previous week. In August 2015, new shoots in pine and spruce were entirely developed and deciduous trees had dense green foliage.

# 2.4. Radiometric match of the LiDAR datasets, RQ1

It was important to verify that the repeated LiDAR observations of unchanged scene targets are similar so that observed signal differences in vegetation can be associated with deviations in their geometricoptical properties. We differentiated between 'hard' and 'soft' targets (Fig. 2) and the radiometric match was evaluated in hard targets. The threshold of peak amplitude (pA) that triggered the WF-storage was 9-10 in all campaigns (Fig. 3). This showed in powerline cables, which were oriented in direction of the flight lines. This means that incidence angle effects were irrelevant because of the circular cross-section of the cables. Fig. 3 illustrates how a decreasing number of WFs was available as range (R) increased. The patterns imply that the amplitude scale is linear in weak signals, if an offset of 2 is applied (ratio-scale). Using the offset, pA of the strongest returns decreased at the rate of  $(R/R_{ref})^3$  (we used 750 m for  $R_{ref}$ ). In extended targets the rate was  $(R/R_{ref})^2$ , which matches the theory (Wagner, 2010). If the amplitude values are not ratio-scale of observations of received power, range-normalization using the radar equation fails.

Fig. 3 illustrates how pA in cables varied considerably, which is explained by the varying cable-pulse intersection geometry. The withinfootprint energy profile of the transmitted pulse of LMS-680i was deemed Gaussian in Korpela et al. (2013) and WF-storage was triggered by the cable at R above 900 m only if the pulse was perfectly aligned



**Fig. 3.** Peak amplitude values of cable WFs as a function of range. The dashed lines represent theoretical spherical losses in a linear target. The dotted line is the storage-triggering threshold of the receiver.

with the cable. We estimated, by comparing pulses reflecting from bitumen and the highly reflective cables, that a 3–4-% silhouette area by green foliage (at the center of the pulse) triggered the WF-storage in LMS-Q680i at a R of 750 m.

WFs in LMS-Q680i are characterized by 'ringing' (Fig. 2) (Korpela et al., 2020). WFs have false peaks following a strong signal at 11-ns delay. The pA of such pseudoechoes is 5–8 at maximum. Their strength correlates positively with the strength of the preceding true signal. Ringing creates false 'below-ground' and 'weak second canopy echoes' and causes bias in energy features (sums of amplitudes). We therefore applied a threshold (pA of 7) to distinguish 'true backscattering' from ringing.

All campaigns showed a similar influence by R in signal levels. Fig. 4 shows data from gravel, in which quadratic spherical losses explained the decrease of signals, whereas in old asphalt, the signals fell more than spherical losses would explain, when SZA exceeded 15°. A specular component was present and our between-campaign comparisons were



Fig. 2. WFs of 'hard' and 'soft' targets. The two hard targets comprise of a linear target (cable, crossbar of a football goal) followed by a well-defined 'hard' surface (grass). Arrows point to pseudoechoes caused by ringing. The two 'soft' targets represent different canopies.



**Fig. 4.** pA × SZA distribution in a 600-m-long gravel road and an asphalt road. In gravel, pA falls 18–20% at SZA of 25°. The decrease is explained by quadratic losses. The sign denotes scan direction 'left' and 'right' of the helicopter.

constrained to SZA  $<20^\circ$  in asphalt.

Compensation of spherical losses (range normalization) was based on the assumption that the amplitudes are ratio-scale observations of instantaneous received power. Only an offset of two was applied to the data as the pA data were in linear relationship with laboratorycalibrated DR intensity. Amplitude values were multiplied by the term (R/750)<sup>2</sup> (Ahokas et al., 2006). R was computed separately for each amplitude so that the normalization coefficient was larger at the base of the tree compared to the top. As noted earlier, the WF-storage threshold influenced the population of targets that remain in the data as R changes (Fig. 3), but this phenomenon of course could not be corrected for.

The stability of returns WFs was assessed using echo width. The influence of SZA on echo width was examined in hard targets. Theoretically, an increase of incidence angle increases echo width as photons of an oblique pulse 'arrive asynchronously at the target'. Echo width was unaffected by SZA in cables. Increase of SZA from 0 to  $30^{\circ}$  increased echo width in frost-covered bitumen and asphalt by 0.2 and 0.1 ns (4% and 2%), respectively. Other planar surfaces and campaigns showed no correlation. In pulses intersecting a vertical metal wall, FWHM increased by 1 (20%) and 0.5 ns (10%) at incidence angles of 70–73° and 60–63°, respectively. All campaigns displayed the same dependence. In wooden benches (rise of 40 cm, Fig. 5), echo widths were 4.5–7.2 ns. Echo width thus measured depth variations correctly as one nanosecond corresponds to a R of 0.15 m. Average echo width of planar surfaces was 4.5 ns (<2% relative variation) in all campaigns. Thus, we concluded that the system WFs were stable.

Between-campaign match of received power (peak amplitude,

energy) was assessed in homogenous targets (Fig. 5). Some of the targets have been used for vicarious calibration of image and LiDAR data (Korpela et al., 2011; Korpela, 2017). Nadir hemispherical-conical reflectance factors (HCRF,  $\rho$ ) of the targets were observed in June 2009 at solar zenith angles of 46–50° and 60–55° and the  $\rho$  are thus off the hot-spot geometry of LiDAR:  $\rho_{asphalt} = 0.22$ ,  $\rho_{grass} = 0.21$ ,  $\rho_{fine \ sand} =$ 0.4,  $\rho_{\text{gravel}} = 0.17$ , and  $\rho_{\text{bitumen}} = 0.06$ . Hence, reflectance calibration was not possible and relative match of campaigns was evaluated instead. Based on field photography and aerial images we found dry patches of asphalt, coarse gravel and powerline cables in the winter data. Targets that were covered by frost (bitumen, sand, grass) displayed 50-70% lower signals compared to summer. Wet patches of asphalt displayed 20-30% lower signals compared to the dry areas. Similar offset was present in summer data, when comparing old asphalt with paving repairs. The winter data matched the summer acquisitions in cables, dry asphalt and gravel sites such that the mean values deviated 3-7%. Differences between summer acquisitions were below 5% except for grass (B and C in Fig. 5).

# 2.5. Forest reference - plots and individual trees

LiDAR data were collected for canopies inside circular plots and for individual trees (Fig. 6). Plots were selected among those used in Pant et al. (2014), who investigated hyperspectral images. Selected plots were constrained to represent pure pine (n = 47), spruce (n = 40) and birch (n = 19) canopies. Radius was 15–20 m. The age of stands was assessed in aerial images, but the estimates are not accurate in drained pine bogs and in old forests. Age of birch stands was 25-40 years, while the mean age of pine and spruce was 55 and 65 (20-120, 20-135), respectively. The selected stands had escaped thinning operations 2011-2015. A separate set of 15 plots was placed in a 90-year-old pine forest in Lapinkangas. It is a homogenous sparsely populated stand that lacks an understory tree layer (Fig. 7) and was included for assessing the precision of the plot-level WF mean features in a homogenous forest. Lapinkangas was used in Korpela (2008) for analyzing 1064-nm LiDAR signals of ground lichens. The bottom flora consists of a few moss species, reindeer lichens, heather, lingonberry and litter.

Tree-level data was needed to expand the species list and to have more age variation in birch. We used trees of two field plots and additional trees, which were positioned (treetop coordinates by LiDAR monoplotting, see Fig. 1 in Korpela et al., 2009) using visual interpretation of image and LiDAR data (Table 2).

Field plots 'Old Growth' (OG, 1.1 ha, N61.8314°, E24.3082°) and 'Intermediate' (IM, 0.7 ha, N61.8346°, E24.3181°) represent mature 100–140-yr-old and 45–50-yr-old trees. Plots were established using a protocol in which treetops are first positioned in airborne data and later in the field using triangulation and trilateration (Korpela et al., 2007).



Fig. 5. Radiometric targets in winter images: A fine sand, B fertile lawn, C worn lawn, D gravel, E bitumen, F crossbar, G wooden benches, H asphalt and I powerline cables. Other calibration targets were powerline cables, asphalt, sand pits and gravel roads in different parts of the study area. The ground photo was taken during the winter LiDAR campaign in 2011 and shows frost-covered grass (C), wooden benches (G) and football goals (F).



**Fig. 6.** Reference trees (small symbols) and circular plots (large symbols) in an aerial image from June 2015. White dotted lines represent flight lines of LiDAR. Field plots OG and IM and the Lapinkangas pine forest are marked separately.



Fig. 7. Lapinkangas in August 2012.

Tree reference data. OG and IM are field plots. VISU and DSP trees were measured by visual interpretation of aerial images and LiDAR. DSP tree set consists of 159 spruces that were identified as dead in 2011 (57 were broken or felled by 2015) and 362 spruces that were observed as dead in 2015 (of these 226 and 154 were dead in 2013 and 2011, respectively).

Tree set	Type and time of observation	Sample size by species class	Height range by class, m
OG	Field plot, 2015	$\begin{array}{l} n_{Pine} = 102,  n_{Spruce} = 336, \\ n_{Birch} = 25 \end{array}$	20–30, 5–33, 21–30
IM	Field plot, 2013	$n_{\text{Pine}} = 153, n_{\text{Spruce}} = 297,$ $n_{\text{Birch}} = 44$	13–22, 5–22, 12–23
VISU	Visual, 2011–13	$n_{Pine} = 352, n_{Spruce} = 170,$ $n_{Birch} = 668$ $n_{Alder} = 148, n_{Larch} = 366,$	12–35, 13–34, 13–31 15–25, 14–32.
DSP	Visual 2011, 2015	$\begin{array}{l} n_{Aspen} = 167 \\ n_{Dead2011} = 159,  n_{Dead2015} \\ = 362 \end{array}$	15–31 13–33, 10–40

Understory tree layer in both plots is sparse and consists of spruce, rowan (*Sorbus aucuparia* L.) and downy birch. Blueberry (*Vaccinium myrtillys*, L.) is the dominant shrub and a contiguous moss layer comprises of mosses such as the 'stairstep moss' (*Hylocomium splendens*, (Hedw.) Schimp).

Tree sets collected by visual interpretation are referred to as VISU and DSP (Table 2). Set VISU has 30–125-yr-old pines, spruces and birches. Alders are from two planted stands and most larches are from five 25–100-yr-old stands. Aspen is rare and occur in small clones, which were identified in leaf-off aerial images of 2011. Set DSP consists of dead standing spruces in two groups. All dead spruces were determined the last time point when the tree was alive using a time-series of aerial images (Fig. 9). Trees of group DSP<sub>2011</sub> represent 13–33-m-high dominant trees (n = 159) in the vicinity of plots OG and IM and they were identified as dead in the first LIDAR campaign in 2011. A total of 57 were felled or broken before the last campaign in 2015. DSP<sub>2015</sub> trees (n = 362) are scattered across the scanned area and were identified as dead in the last LiDAR campaign of 2015. Of the DSP<sub>2015</sub> trees 72 and 136 had died between the LiDAR campaigns.

# 2.6. 3D crown models for tree-level analyses

To assign WF sequences to each tree, we applied crown models that predict the crown radius at a given relative height (see details in Korpela et al., 2011, Korpela et al., 2023). LiDAR of 2013 was used for the modeling. The operator viewed multiple aerial images and pointed the tree's apex in one to measure the 3D coordinates by monoplotting. Given height and species, an approximate envelope model was computed first and was then refined (weighted least squares regression) to the point cloud data. The operator altered iteratively the expected values of the model parameters until the model fitted the point cloud and crown in the image. The goodness of fit was evaluated visually.

# 2.7. Extraction of WF attributes and computation of WF features for trees and plots

Because the received WFs consisted of 1–3 sequences, we first formed a continuous WF for each transmitted pulse by concatenating the sequences. Pauses between sequences were assigned no-backscattering values (Fig. 12). The XYZ-coordinates of a WF amplitude were defined by a time offset (distance along the pulse vector) between the first amplitude and DR echo. These naïve coordinates were 10-cm accurate in hard targets, which justifies their use in 5–35-m-high trees. The binary LiDAR files had the time offsets.

Each tree was searched for pulses that potentially had intersected the crown (Fig. 10). Given the crown model and the geometry of each pulse, it was possible to iteratively solve ray-surface intersections in 3D. These were used to split the WF between crown, understory and ground

segments. Because of the convolution, the segments had small overlap near P<sub>exit</sub> and P<sub>Ground</sub> as we did not carry out explicit WF decomposition (Roncat et al., 2014). For example, WF<sub>Ground</sub> was assigned amplitude values at the height of  $\pm 1.25$  m (elevation model). Because real crowns are not circular-symmetric opaque surfaces, there were pulses near the outer crown perimeter, which intersected the model, but displayed no backscattering and were rejected. Oblique pulses could show backscattering preceding P<sub>enter</sub> due to a neighboring tree or a single distinct branch. Because we did not know the crown base height, we assumed a fixed crown ratio, which was 55% for spruce and 40% in other species (average values in the local forests). This is a compromise as relative crown length depends on the species and stand history. The crown models were likely too short in spruce (shade-tolerant) in sparse stands, whereas the models may exaggerate crown length in dense pine and birch (light-demanding) canopies.

In circular plots, crown base height (CBH) was defined subjectively for each plot using height distributions of first returns of the 2013 LiDAR data (Fig. 11).

Height distributions in Fig. 11 were computed using all pulses. However, most analyses regarding phenology were constrained to pulses that displayed crown backscattering. Table 3 lists WF attributes that were derived for each pulse and Fig. 12 illustrates them. We adopted many attributes from Hovi et al. (2016), who used 7.8-10.5-ns-long pulses and searched the WFs for so-called first-return noise-exceeding amplitude sequences (NEAS), which in their ALS60 data were fewer compared to LMS-Q680i. To maintain comparability, we implemented the NEAS approach also. Attributes MinRelDist, pADist, pARelDist and SZA were mainly included for control purposes. For example, average tree-level pADist was expected to correlate with crown diameter. Similarly, the distribution of SZA was assumed to be affected by tree height as suppressed trees are more likely occluded at high SZA. Many of the attributes are correlated. For example, strong negative correlation of eCROWN and eGND was observed in stands that lack an understory and the tree layer has a single species. Fig. 13 shows their correlation in a larch stand. The correlations however differ between phenostates as the backscattering of leaf-off crowns and the wet ground differ substantially from the two summer phenostates, which display a similar dependence.

The offset of 2 was subtracted from all amplitude values and noise was reduced by accepting only NEASs that were longer than 5 ns. Peak amplitude of 8 was required for a valid NEAS (due to ringing). Moderate

# Table 3

WF attributes of pulses intersecting crowns. Attributes marked with \* are from Hovi et al. (2016). Attributes marked with \*\* were not available in circular plots as they use the crown model. Point pA is the XYZ-position of pA, the peak amplitude.

Attribute	Definition
eTOTAL	Total energy. Sum of amplitude values in the entire WF
eCROWN	Crown energy. Sum of amplitude values assigned to WF <sub>Crown</sub>
eNEAS*	Energy of the (first-return) noise-exceeding amplitude sequence,
	NEAS
eUNDER	Understory energy. Sum of amplitude values assigned to WF <sub>Understory</sub>
eGND	Ground energy. Sum of amplitude values assigned to WF <sub>Ground</sub>
nCROWN	Number of local maxima in WF <sub>Crown</sub>
nNEAS*	Number of local maxima in the (first) NEAS
pA*	Maximum amplitude in the NEAS, 'peak amplitude' (>7 for a valid
	NEAS)
FWHM*	Width of the echo defined by pA, nanoseconds
INEAS*	Length of the (first) NEAS, nanoseconds (constrained to be $>5$ )
pDist	Mean distance between local peaks in WF <sub>Crown</sub> , meters
MinRelDist**	Minimum relative horizontal pulse-trunk distance inside the crown,
	0–1
pADist**	Horizontal distance between trunk and point pA, meters
pARelDist**	Horizontal distance between trunk and point pA, relative to crown
	radius, 0–1
EQ50	Relative distance of the energy median from the start of the NEAS,
	0–1
SZA	Scan zenith angle, degrees

low-pass filtering preceded the detection of local maxima (peaks). The number of peaks (nNEAS, nCROWN) and their mean distance (pDist) were based on the filtered WF. WF features were distribution metrics of the attribute values. For example, m\_FWHM and s\_FWHM are the arithmetic mean and standard deviation features of the echo width attribute in pulses that had intersected a plot or a tree. The WF attributes of Table 3 were compared between Leica ALS60 and LMS-Q680i in Korpela et al. (2023).

#### 3. Results of experiments

# 3.1. Between-campaign differences of WF features in deciduous trees, RQ2

#### 3.1.1. 25-40-year-old birch plots

In birch plots, winter features differed substantially from leaf-on data (Table 4). Height of points pA was 0.96 m lower in 11/2011 compared to 5/2013, while the increase from 5/2013 to 8/2015 was 1.0 m. The annual height growth is 0.3–0.4 m, which implies that winter WFs underestimate canopy height. The proportion of pulses reaching the ground was high in leaf-off canopy (54.2%) and decreased from 22.9% to 18.3% in the summer datasets because canopy closure increased between the acquisitions.

Crown backscattering was the lowest in winter. eCROWN and eNEAS increased 108 and 160% from winter to early summer. Many of the birch stands have a spruce understory, which may explain why eUNDER did not vary between acquisitions. Average eCROWN of all pulses increased 5% during the summer, but the increase was only 1% in pulses that displayed crown backscattering only. While eCROWN increased, pA decreased between summer acquisitions. The decrease was compensated by INEAS. Leaf-off WF peaks were wider (FWHM) and had a 'softer start' (EQ50) compared to leaf-on WFs. FWHM increased 5% between summer campaigns. Feature pDist, which is the average distance between WF

#### Table 4

Mean values of pulse proportions (P) and WF attributes in birch plots and their relative change (%) between winter and early summer (WE) and between early and late summer (EL). Values in parentheses are standard error (SE) estimates.

	Winter	Early	Late	WE	EL
P(h < 2 m), all pulses,	54.2 (2.4)	21.9 (2.3)	17.3 (2.3)	-60	$^{-21}$
%					
Height, point pA, m	13.7 (0.5)	14.6 (0.5)	15.6 (0.5)	7	7
P, crown only, %	8.5 (1.1)	44.1 (0.9)	47.3 (1.4)	419	7
P, crown + gnd, %	58.2 (3.8)	33.2 (2.5)	30.4 (2.6)	-43	-8
P, crown + under, %	23.6 (1.9)	15.7 (1.5)	13.2 (1.1)	-33	$^{-16}$
P, crown + under + end. %	9.7 (2.1)	7.1 (1.4)	9.1 (1.8)	-27	28
eTOTAL	467 (14)	746 (10)	739 (10)	60	-1
eCROWN, crown-					
only	426 (16)	646 (6)	652 (7)	52	1
eCROWN	258 (6)	537 (8)	564 (11)	108	5
eNEAS	181 (4)	470 (8)	476 (9)	160	1
eUNDER, no ground	168 (10)	142 (10)	138 (8)	$^{-15}$	-3
eUNDER, with					
ground	126 (5)	153 (6)	169 (6)	21	10
eGND, all	208 (9)	366 (9)	328 (10)	76	$^{-10}$
eGND, no understory	223 (8)	406 (6)	363 (10)	82	$^{-11}$
eGND, with					
understory	175 (11)	297 (10)	263 (8)	70	$^{-11}$
nCROWN	2.11 (0.04)	1.93 (0.03)	2.14 (0.03)	-8	11
pDist, m	2.54 (0.05)	2.28 (0.03)	2.35 (0.03)	$^{-10}$	3
pA	24.0 (0.6)	63.7 (1.0)	60.1 (1.1)	165	-6
FWHM, ns	8.34 (0.07)	7.12 (0.04)	7.46 (0.05)	$^{-15}$	5
lNEAS, ns	12.1 (0.15)	16.1 (0.20)	17.2 (0.20)	33	7
SZA crown-only,					
degrees	14.3 (0.70)	13.9 (0.69)	13.0 (0.46)	-3	-7
SZA, degrees	14.2 (0.5)	13.6 (0.6)	12.7 (0.4)	-4	-7
	0.419	0.374	0.382		
EQ50	(0.001)	(0.001)	(0.001)	$^{-11}$	2
Pulses per plot	8002	16,385	16,178		

peaks was the largest in winter (2.58 m) although trees were the shortest in this first campaign.

eGND increased 70–80% between winter and summer and showed a similar 10% decrease from early to late summer, which was observed in pine and spruce plots (Table 8). Most likely this 'summer decrease' is explained by the 3-year growth of crowns (interlaced crowns change the traits of pulses reaching ground) rather than by reflectance properties of the bottom flora.

#### 3.1.2. Tree-level analyses

Table 5 shows the results of mean WF attributes for aspen, alder, larch and birch. The mean values by species are compared in Table 6 and the relative changes between acquisitions are shown in Table 7.

Winter backscattering in larch differed substantially from the other deciduous species. Leaf-off larch displayed the strongest single WFs of all datasets. Average eCROWN, pA and eNEAS increased only 7–34% from winter to early summer, while the increase in the other species was 56–142%. Larch bark has a high 1550-nm reflectance (Rautiainen et al., 2018). Table 7 illustrates also how aspen deviated from other deciduous species in how eCROWN, eNEAS and pA changed during the summer. In aspen, these features increased by 16–18% from early to late summer and the likely explanation is the delayed development of some aspen clones in the early summer LiDAR of 2013. In the other species, crown backscattering changed very little between the summer acquisitions.

The return peaks were wider in leaf-off data (FWHM, 4–11%) compared to leaf-on data. An exception was aspen, which displayed the lowest FWHM in winter. Aspen has upright branches and highly vertical leaf orientation, which explains the anomaly i.e. explains the large FWHM. EQ50 peaked in the winter in all species. Leaf-off return pulses had a 'slower rise' compared to leaf-on pulses. Pulses also penetrate deeper into the crown in leaf-off crowns as indicated by features Min-RelDist and pARelDist that show minima in winter. (Table 5, Table 6).

Winter eGND was lower compared to summer, which is explained by the wet conditions. eUNDER in leaf-off data showed also high values in larch (Table 6), and is explained by the dead branches, which remain attached to the trunks. As shown in correlation analyses (Section 3.4), the number of return peaks (nCROWN) correlates strongly with tree height, while nNEAS is less affected by height. In larch, nNEAS was the highest in winter (Table 6), while the opposite was true for other deciduous species. Again, the high reflectance of bark in larch likely explains this difference.

# 3.2. Between-campaign differences of WF features in evergreen conifers and dead spruce, RQ2 and RQ3

# 3.2.1. Pure pine and spruce canopies in circular plots

There were 47 and 40 plots in pine and spruce stands and 15 plots in the 90-yr-old Lapinkangas (LK) pine forest. In all datasets, tree growth 2011–2015 increased first-return heights and decreased pulse penetration to ground (Table 8). Although the campaigns were separated by 18 and 27 months, the relative changes of WF features are given for two transitions – i) 'winter to early summer' and ii) 'early summer to late summer' (Table 9).

In pine (Table 8, Table 9), ground energy (eGND) increased 120-130% between winter and early summer. In Lapinkangas, the same was observed in pulses that did not intersect crowns (not tabulated). Because of high absorbance of the wet ground, the proportion of pulses that displayed crown-only scattering was high in winter. Total energy of the pulses (eTOTAL) was the lowest in winter because of the wet ground. Canopy backscattering increased 7-8% from winter to summer. However, following an increase, eCROWN, eNEAS and peak amplitude (pA) in pine decreased 5-9% from early to late summer. Hence, the winter and late summer canopy signals were at the same level. The geometric features (FWHM, EQ50, INEAS, nCROWN, pDIST) exhibited very small differences between the three campaigns in pine. Center of gravity (EO50) and echo width (FWHM) were the lowest in early summer. The length of the first-return NEAS (INEAS) is in positive correlation with energy features and showed therefore a similar pattern of relative changes.

Fig. 14 shows the relative frequency distributions of energy features in the 15 plots of the homogenous Lapinkangas forest (Fig. 7). The radius of the plots was 20 m, and there were approximately 44 dominant pines per plot (350 stems ha<sup>-1</sup>). In Lapinkangas, the average coefficients of variation of plot-level estimates of eCROWN, eTOTAL and eGND were 2.2%, 2.6% and 4.8%, respectively. In the 47-plot heterogenous pine data, the corresponding estimates of precision were 7.7%, 8.0% and

#### Table 5

Average values of mean WF features in birch, aspen, alder and larch. Values in parentheses are standard error (SE) estimates. SEs of EQ50 (not tabulated) were all 0.001–0.002.

	Winter				Early summer				Late summer			
Feature	Birch	Aspen	Alder	Larch	Birch	Aspen	Alder	Larch	Birch	Aspen	Alder	Larch
n(trees)	620	167	148	365	620	167	148	365	539	167	148	364
eCROWN	285 (3)	236 (7)	252 (4)	523 (8)	507 (2)	391 (6)	546 (6)	560 (3)	515 (2)	481 (6)	522 (7)	550 (4)
eNEAS	206 (2)	177 (5)	199 (3)	455 (6)	457 (2)	344 (6)	496 (7)	523 (3)	459 (2)	434 (6)	488 (7)	504 (4)
eTOTAL	543 (2)	559 (11)	514 (7)	870 (10)	680 (2)	589 (5)	765 (6)	738 (3)	667 (3)	634 (7)	674 (8)	767 (3)
pA	26.3 (0.4)	27.1 (0.5)	26.9 (0.3)	47.8 (0.8)	59.3 (0.4)	48.2 (0.8)	65.1 (0.9)	68.4 (0.4)	56.9 (0.4)	58.9 (0.8)	66.6 (0.9)	61.9 (0.5)
eUNDER	212 (2)	260 (6)	203 (4)	376 (6)	170 (2)	173 (3)	172 (3)	196 (2)	161 (2)	161 (3)	131 (3)	204 (3)
eGND	198 (1)	188 (4)	191 (3)	175 (2)	290 (3)	227 (5)	264 (6)	284 (4)	254 (3)	211 (9)	218 (9)	280 (4)
PCDOWN	2.28	2.07	2.18	2.37	2.01	2.18	2.27	2.04	2.14	2.20	2.13	2.18
lickown	(0.01)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
DNEAC	1.40	1.25	1.36	1.76	1.50	1.41	1.57	1.55	1.57	1.49	1.52	1.60
nNEAS	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
EMILINA	8.09	6.84	7.27	7.94	7.25	6.97	7.00	7.07	7.38	6.98	6.87	7.27
FWFIN	(0.02)	(0.03)	(0.03)	(0.06)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
EQ50	0.421	0.417	0.421	0.423	0.374	0.393	0.376	0.378	0.377	0.385	0.380	0.387
<b>p</b> Dict	2.07	2.15	2.06	1.88	2.00	2.09	2.11	1.88	2.00	2.04	2.05	1.93
pDist	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
INFAC	13.0	10.2	11.8	18.5	16.7	14.0	16.9	17.3	17.4	15.9	16.4	17.7
INEAS	(0.06)	(0.14)	(0.13)	(0.18)	(0.06)	(0.13)	(0.14)	(0.10)	(0.07)	(0.16)	(0.19)	(0.14)
MinDolDict	0.48	0.50	0.51	0.49	0.53	0.54	0.54	0.53	0.54	0.55	0.53	0.53
MIIIKeiDist	(0.002)	(0.005)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)
m A D al Diat	0.63	0.63	0.67	0.62	0.75	0.74	0.77	0.74	0.79	0.80	0.89	0.78
pareiDist	(0.002)	(0.006)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.003)
SZA	14.7 (0.08)	14.4 (0.1)	12.5 (0.1)	16.6 (0.1)	15.3 (0.09)	14.8 (0.2)	12.8 (0.2)	16.5 (0.1)	15.4 (0.10)	15.3 (0.2)	15.0 (0.2)	15.0 (0.2)

Relative differences of mean WF attributes in aspen, alder, larch and birch. The differences were computed relative to birch.

Feature	Winter				Early summer				Late summer			
	Birch	Aspen	Alder	Larch	Birch	Aspen	Alder	Larch	Birch	Aspen	Alder	Larch
eCROWN	1.00	0.83	0.89	1.84	1.00	0.77	1.08	1.10	1.00	0.93	1.01	1.07
eNEAS	1.00	0.86	0.97	2.21	1.00	0.75	1.09	1.14	1.00	0.95	1.06	1.10
eTOTAL	1.00	1.03	0.95	1.60	1.00	0.87	1.13	1.09	1.00	0.95	1.01	1.15
pA	1.00	1.03	1.03	1.83	1.00	0.81	1.10	1.15	1.00	1.03	1.17	1.09
eUNDER	1.00	1.22	0.96	1.77	1.00	1.02	1.01	1.15	1.00	1.00	0.81	1.27
eGND	1.00	0.95	0.97	0.88	1.00	0.78	0.91	0.98	1.00	0.83	0.86	1.10
nCROWN	1.00	0.91	0.96	1.04	1.00	1.08	1.13	1.01	1.00	1.03	1.00	1.02
nNEAS	1.00	0.89	0.97	1.25	1.00	0.94	1.05	1.03	1.00	0.95	0.97	1.02
FWHM	1.00	0.85	0.90	0.98	1.00	0.96	0.97	0.98	1.00	0.95	0.93	0.99
EQ50	1.00	0.99	1.00	1.00	1.00	1.05	1.01	1.01	1.00	1.02	1.01	1.02
pDist	1.00	1.04	0.99	0.91	1.00	1.05	1.06	0.94	1.00	1.02	1.03	0.97
INEAS	1.00	0.79	0.91	1.43	1.00	0.84	1.01	1.03	1.00	0.91	0.94	1.01
MinRelDist	1.00	1.05	1.07	1.03	1.00	1.02	1.02	1.00	1.00	1.01	0.97	0.98
pARelDist	1.00	1.00	1.07	0.99	1.00	0.99	1.03	0.99	1.00	1.01	1.12	0.98

# Table 7

Relative change (%) of mean WF features in deciduous trees from winter to early summer (WE) and from early to late summer (EL).

	WE				EL				
Feature	Birch	Aspen	Alder	Larch	Birch	Aspen	Alder	Larch	
eCROWN	94	62	56	7	2	16	-4	-2	
eNEAS	142	84	65	15	1	18	-2	-4	
eTOTAL	25	6	29	-19	$^{-2}$	6	$^{-12}$	4	
pA	122	78	79	34	-5	17	2	$^{-11}$	
eUNDER	-16	-43	-8	-106	-5	-7	-21	5	
eGND	49	20	42	38	-16	-6	-16	-2	
nCROWN	-13	5	4	-16	6	1	-7	7	
nNEAS	8	12	12	-14	5	5	$^{-3}$	3	
FWHM	$^{-12}$	2	$^{-3}$	-12	2	0	-2	3	
EQ50	-11	-6	-11	-12	1	$^{-2}$	1	2	
pDist	-4	-3	3	0	0	-3	$^{-3}$	3	
INEAS	37	32	28	-7	5	11	-3	2	
MinRelDist	11	8	6	8	2	1	$^{-3}$	0	
pARelDist	19	16	16	16	6	8	8	5	

# Table 8

Mean values and (standard errors) of pulse proportions (P) and WF attributes in pine and spruce plots. Proportion of pulses reaching the ground, P(h < 2 m), is computed using all pulses, while other entries are based on pulses with crown backscattering. 'Winter', 'Early S' and 'Late S' refer to the campaigns of 11/2011, 5/2013 and 8/2015. 'Crown only' refers to pulses that did not display any understory (under) or ground (gnd) scattering.

	Spruce 20–135-year-old, 40 plots			Pine 20–120-ye	ar-old, 47 plots		Lapinkangas pine forest, 15 plots			
Variable/campaign	Winter	Early S	Late S	Winter	Early S	Late S	Winter	Early S	Late S	
P(h < 2 m), all pulses, %	29.4 (2.0)	29.5 (1.6)	26.9 (1.6)	37.6 (2.2)	34.5 (2.2)	30.9 (2.2)	50.8 (2.0)	49.9 (2.2)	45.0 (2.1)	
Height, point pA, m	15.2 (0.6)	15.6 (0.6)	16.2 (0.6)	12.4 (0.5)	12.6 (0.5)	13.2 (0.5)	16.8 (0.2)	17.1 (0.2)	17.4 (0.2)	
P, crown only, %	64.2 (1.6)	58.4 (1.4)	59.9 (1.1)	39.3 (1.8)	30.8 (1.6)	33.7 (1.5)	53.9 (0.8)	40.5 (0.7)	39.2 (0.7)	
P, crown + gnd, %	15.0 (0.8)	24.4 (0.9)	24.5 (0.9)	35.3 (1.3)	42.6 (1.9)	42.2 (1.9)	40.5 (0.8)	54.2 (0.8)	54.6 (1.1)	
P, crown + under, %	12.6 (1.2)	12.6 (1.4)	11.4 (1.0)	18.5 (1.6)	22.5 (1.7)	19.4 (1.3)	3.9 (0.3)	4.5 (0.3)	4.7 (0.3)	
P, crown + under + gnd,										
%	8.2 (0.9)	4.6 (0.5)	4.2 (0.5)	7.0 (0.7)	4.1 (0.6)	4.7 (0.8)	1.7 (0.2)	0.9 (0.1)	1.5 (0.2)	
eTOTAL	613 (10)	649 (5)	622 (5)	558 (7)	752 (9)	688 (7)	597 (3)	786 (4)	727 (5)	
eCROWN, crown-only	603 (11)	584 (7)	562 (6)	569 (12)	616 (9)	559 (8)	635 (5)	695 (5)	640 (4)	
eCROWN	546 (10)	520 (7)	504 (6)	448 (7)	477 (5)	451 (5)	514 (4)	545 (4)	508 (3)	
eNEAS	444 (7)	417 (4)	403 (4)	400 (6)	427 (4)	398 (4)	440 (3)	471 (4)	434 (3)	
eUNDER, no gnd	132 (6)	123 (6)	123 (6)	110 (5)	114 (8)	125 (8)	145 (8)	176 (7)	158 (5)	
eUNDER, with gnd	182 (6)	157 (4)	158 (4)	124 (3)	133 (4)	143 (6)	130 (4)	143 (5)	135 (3)	
eGND, all	173 (5)	314 (4)	290 (5)	173 (3)	382 (7)	338 (6)	174 (3)	400 (4)	356 (5)	
eGND, no under	184 (5)	337 (4)	305 (5)	181 (3)	400 (7)	353 (6)	175 (3)	407 (3)	363 (4)	
eGND, with under	162 (6)	270 (5)	262 (7)	158 (3)	347 (8)	309 (8)	161 (4)	325 (10)	288 (11)	
nCROWN	2.11 (0.03)	2.11 (0.03)	2.12 (0.02)	1.94 (0.02)	1.94 (0.03)	1.97 (0.03)	2.12 (0.02)	2.07 (0.01)	2.11 (0.01)	
pDist, m	2.28 (0.04)	2.33 (0.04)	2.37 (0.04)	1.90 (0.01)	1.93 (0.01)	1.97 (0.01)	2.07 (0.01)	2.10 (0.01)	2.13 (0.01)	
pA	65.7 (1.2)	62.8 (0.7)	60.8 (0.7)	49.6 (1.1)	54.0 (0.8)	50.7 (0.8)	59.0 (0.6)	64.9 (0.7)	59.1 (0.7)	
FWHM, ns	6.49 (0.04)	6.45 (0.04)	6.47 (0.04)	7.42 (0.06)	7.28 (0.05)	7.29 (0.05)	6.80 (0.02)	6.69 (0.02)	6.78 (0.02)	
lNEAS, ns	14.6 (0.10)	14.2 (0.11)	14.0 (0.10)	16.3 (0.10)	16.6 (0.17)	16.2 (0.17)	15.9 (0.11)	15.9 (0.07)	15.5 (0.07)	
SZA crown only, degrees	15.1 (0.36)	14.4 (0.36)	14.0 (0.49)	15.5 (0.41)	15.1 (0.29)	14.9 (0.24)	12.2 (0.3)	12.7 (0.4)	12.5 (0.3)	
SZA, all, degrees	14.8 (0.3)	14.1 (0.3)	13.7 (0.5)	15.0 (0.41)	14.5 (0.25)	14.5 (0.23)	12.3 (0.3)	12.8 (0.3)	12.7 (0.4)	
	0.385	0.387	0.388	0.383	0.376	0.379	0.377	0.372	0.377	
EQ50	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	
Pulses per plot	12,008	12,184	11,780	12,005	11,767	12,137	8470	9004	10,349	

Relative change (%) of pulse proportions (P) and mean WF attributes from winter to early summer and from early to late summer in pine (P, LK) and spruce (S) plots.

	Winter	$\rightarrow$ Early	S	Early $S \rightarrow Late S$			
Feature	s	Р	S Early S → Late S   LK S P LK   -2 -9 -10 -1   2 4 4 2   -25 3 10 -3   34 0 -1 1   15 -10 -14 4   -47 -9 12 67   32 -4 -9 -8   9 -4 -9 -8   6 -3 -5 -7   7 -3 -7 -8   21 0 10 -1   10 1 8 -6   130 -8 -12 -1   102 -3 -11 -1   -2 0 1 2 2   2 2 2 1   100 -3 -6 -6   -2 0 0 1 2   2 2 2	LK			
P(h < 2 m), all pulses, %	0	-8	-2	-9	$^{-10}$	-10	
Height, point pA, m	3	2	2	4	4	2	
P, crown only, %	-9	-22	-25	3	10	-3	
P, crown $+$ gnd, %	63	21	34	0	$^{-1}$	1	
P, crown + under, %	0	22	15	$^{-10}$	-14	4	
P, crown + under + gnd, %	-44	-41	-47	-9	12	67	
eTOTAL	6	35	32	-4	-9	-8	
eCROWN, crown-only	-3	8	9	-4	-9	-8	
eCROWN	-5	6	6	-3	-5	-7	
eNEAS	-6	7	7	-3	-7	-8	
eUNDER, no gnd	-7	4	21	0	10	$^{-10}$	
eUNDER, with gnd	-14	7	10	1	8	-6	
eGND, all	82	121	130	-8	$^{-12}$	$^{-11}$	
eGND, no under	83	121	133	-9	$^{-12}$	$^{-11}$	
eGND, with under	67	120	102	-3	-11	$^{-11}$	
nCROWN	0	0	$^{-2}$	0	1	2	
pDist, m	2	2	2	2	2	1	
pA	-4	9	10	-3	-6	-9	
FWHM, ns	$^{-1}$	$^{-2}$	$^{-2}$	0	0	1	
lNEAS, ns	-3	2	0	$^{-1}$	$^{-2}$	-3	
SZA crown-only, degrees	-5	-3	4	-3	$^{-1}$	$^{-2}$	
SZA, degrees	-5	-3	4	$^{-3}$	0	$^{-1}$	
EQ50	1	-2	$^{-1}$	0	1	1	

12.4%. The histograms in Fig. 14 show the offsets between early and late summer, which were -7, -8 and -11% for eCROWN, eTOTAL and eGND, respectively. The relative change of eGND in pulses that reached the forest floor through canopy openings was -4% (not shown). Similarly, asphalt and gravel surfaces in the vicinity displayed a relative change of -3% (not shown). These findings suggest that the decrease of signals between early and late summer in trees and the forest floor is not explained entirely by some sensor or atmospheric effect. We thus observed a small (3-6%) decrease of crown backscattering in pine during the summer. The 7-9-% increase of canopy backscattering between winter and early summer could not be corroborated by any local reference surface. The wet asphalt and gravel roads showed 45 and 17% lower values in winter compared to early summer. It is possible that the wintering pine shoots were moist. On the other hand, pine stamens were blooming during the early summer campaign, which may have caused 'an early summer peak' in the return signals of pine. Lower winter signals could be explained by a lower silhouette area of pine needles (change of needle angles) in the winter, but we found no research to support this hypothesis. The dominance of older needle cohorts (with larger needle angles) in the winter phenostate (Stenberg et al., 1994) would create an opposite winter-early summer anomaly.

In spruce, crown backscattering (eNEAS, eCROWN, pA) was the strongest in winter and the weakest in late summer. The relative decrease from winter to early summer was 5-7% and signals decreased further by 3-4% between early and late summer. The corresponding changes in pine were 6-9% (increase) and 5-9% (decrease). FWHM and EQ50 in spruce did not show differences between acquisitions. eUNDER increased 7-14% between winter and early summer and did not change during the summer. The presence of suppressed deciduous trees (rowan, downy birch) in spruce stands may in part explain this finding. In spruce, eTOTAL varied considerably less between acquisitions compared to pine. eGND increased 82% from winter to summer, which is less compared to pine (125%). In summer, eTOTAL was 10-14% higher in pine compared to spruce, while in winter spruce displayed a 10% higher eTOTAL. Differences of ground flora between pine and spruce are likely explanations, but the effect may also be due to between-species differences of (undetected) canopy transmission losses.

Table 10 shows the relative differences of mean features between the

#### Table 10

Relative differences (%) of mean attributes between the two pine strata (47 plots vs. Lapinkangas forest) and between pine and spruce plots. A negative value indicates that the value was smaller in the latter group. Wi, ES and LS denote winter, early and late summer, respectively.

	Pine, %			Pine-spruce, %			
WF attribute	Wi	ES	LS	Wi	ES	LS	
eTOTAL	7	5	6	10	-14	-10	
eCROWN, crown-only	12	13	14	6	-5	1	
eCROWN	15	14	13	22	9	12	
eNEAS	10	10	9	11	-2	1	
eUNDER, no ground	32	54	26	20	8	-2	
eUNDER, with ground	5	8	-6	47	18	10	
eGND, all	1	5	5	0	$^{-18}$	$^{-14}$	
eGND, no understory	-3	2	3	2	$^{-16}$	$^{-14}$	
eGND, with understory	2	-6	-7	3	-22	$^{-15}$	
nCROWN	9	7	7	9	9	8	
pDist, m	9	9	8	20	20	20	
pA	19	20	17	32	16	20	
FWHM	-8	-8	-7	-13	-11	$^{-11}$	
lNEAS, ns	$^{-2}$	-4	-4	$^{-10}$	-14	$^{-14}$	
EQ50	$^{-2}$	-1	$^{-1}$	1	3	2	

two pine strata and between pine and spruce. Backscattering of the older pines of Lapinkangas was stronger compared to the 47-plot pine dataset. Similarly, the older Lapinkangas pines displayed lower FWHM (correlation of WF features with age, see Section 3.4). Relative differences of crown backscattering between pine and spruce, were the largest in the winter data. In the summer datasets, average eNEAS did not differ between pine and spruce. In spruce, FWHM was lower compared to pine (see also Fig. 15) and displayed no differences between acquisitions.

# 3.2.2. Tree-level results for pine, spruce and dead spruce

The mean attribute values and their relative change between acquisitions are presented in Table 11 for living pine and spruce. Table 12 shows the results in dead standing spruce separately for sets  $DSP_{2011}$ (observed dead in the images of 2011) and  $DSP_{2015}$  (observed dead in the images of 2015). In living spruce, changes of geometric WF attributes between campaigns were very small. Crown backscattering (eCROWN, eNEAS, pA) decreased from winter to early summer (5–6%) and it decreased further from early to late summer (4%). The same pattern was observed in plot data (Table 9). In pine, crown backscattering increased 1–4% from winter to summer and decreased 7–10% between early and late summer. In plot data, the corresponding changes were 6–9% and 5–9% (Table 9). Changes of geometric WF attributes between phenostates were small in pine. The 2–7-% increase of pARelDist between campaigns is explained by the growth of crowns as the crown models were not altered between acquisitions.

Dead standing spruce displayed much stronger canopy signals (eCROWN, eNEAS, pA) compared to living spruce. Echo width (FWHM) was larger in dead spruce compared to living spruce (6.47-6.51 ns vs. 6.54-6.87 ns). WFs of dead spruce had more WF peaks (nNEAS, nCROWN) compared to living spruce. Pulses penetrate deeper into the crowns of dead spruce (pARelDist) and this 'horizontal penetration' has increased with time in Dead<sub>2011</sub> trees, which is likely due to structural changes (loss of twigs and fine structures, Fig. 8) over time. In addition to pARelDist, also eCROWN, eNEAS, nNEAS, nCROWN, pA and lNEAS all decrease with time in the Dead<sub>2011</sub> trees. eUNDER was higher in dead trees compared to living spruce, because the reflective low branches were visible to the LiDAR. eGND was also higher in dead spruce, which is likely due to lower canopy transmission losses, although changes of the ground flora in response to altered light conditions may also exercise an effect. The between-campaign differences of WF features are small in the Dead<sub>2015</sub> tree set that were observed dead in the last campaign of 2015. This dataset had 361 trees of which 226 and 154 were dead in the 2013 and 2011 campaigns, respectively. In these trees 'aging' had thus a lesser effect. For example, eNEAS varied  $\pm 1\%$ , and changes of eCROWN

Average values of mean WF features and their (standard errors) in living pine and spruce in tree-level data and their relative change (%) from winter to early summer (WE) and from early to late summer (EL).

	Winter 2011		Early summer 20	Early summer 2013		.5	WE, %		EL, %	
Feature	Pine	Spruce	Pine	Spruce	Pine	Spruce	Pi	Sp	Pi	Sp
n(trees)	605	801	605	801	605	797				
eCROWN	484 (3)	503 (2)	491 (2)	475 (2)	455 (2)	456 (2)	1	-6	-7	-4
eNEAS	436 (2)	424 (2)	444 (2)	399 (2)	410 (2)	384 (2)	2	-6	-8	-4
eTOTAL	598 (2)	585 (2)	683 (3)	617 (2)	611 (3)	571 (2)	14	5	-11	-7
pA	57.2 (0.4)	63.1 (0.4)	59.3 (0.4)	59.9 (0.4)	53.4 (0.4)	57.7 (0.3)	4	-5	$^{-10}$	-4
eUNDER	179 (2)	184 (2)	169 (2)	164 (2)	165 (2)	156 (2)	-6	-11	-2	$^{-5}$
eGND	175 (1)	159 (1)	328 (3)	301 (3)	270 (3)	253 (2)	88	89	$^{-18}$	$^{-16}$
nCROWN, n	1.97 (0.01)	2.06 (0.01)	1.96 (0.01)	2.06 (0.01)	1.98 (0.01)	2.06 (0.01)	0	0	1	0
nNEAS, n	1.52 (0.00)	1.41 (0.00)	1.51 (0.00)	1.39 (0.00)	1.51 (0.01)	1.38 (0.00)	$^{-1}$	$^{-1}$	0	$^{-1}$
FWHM, ns	7.05 (0.02)	6.47 (0.01)	6.98 (0.02)	6.48 (0.01)	7.09 (0.02)	6.51 (0.02)	$^{-1}$	0	2	0
EQ50	0.378 (0.000)	0.387 (0.000)	0.372 (0.000)	0.389 (0.000)	0.376 (0.000)	0.390 (0.001)	-2	1	1	0
pDist, m	1.86 (0.01)	2.00 (0.01)	1.87 (0.01)	2.02 (0.01)	1.88 (0.01)	2.02 (0.01)	1	1	1	0
lNEAS, ns	16.2 (0.06)	14.3 (0.05)	16.2 (0.06)	13.9 (0.05)	16.1 (0.07)	13.7 (0.06)	0	-3	-1	$^{-1}$
MinRelDist	0.53 (0.002)	0.50 (0.001)	0.53 (0.002)	0.50 (0.001)	0.52 (0.002)	0.51 (0.001)	1	0	$^{-1}$	1
pARelDist	0.70 (0.002)	0.67 (0.002)	0.73 (0.002)	0.68 (0.002)	0.78 (0.003)	0.71 (0.003)	4	2	7	5
SZA, degr.	13.8 (0.08)	13.4 (0.07)	13.9 (0.09)	13.2 (0.08)	15.7 (0.09)	14.6 (0.08)	1	-2	13	11

#### Table 12

Average values of mean WF features in dead spruce and their relative change (%) from winter 2011 to early summer 2013 ( $11 \rightarrow 13$ ) and from early to late summer ( $13 \rightarrow 15$ ). Trees in groups Dead<sub>2011</sub> and Dead<sub>2015</sub> were identified as dead in the aerial images of 2011 and 2015, respectively. 56 trees in the Dead<sub>2011</sub> set were felled or broken between 2013 and 2015. Similarly, 226 and 154 of the Dead<sub>2015</sub> trees had died before 2013 and 2011, respectively. Values in parentheses are standard error estimates.

Feature	Dead <sub>2011</sub>			Dead <sub>2015</sub>			Dead <sub>2011</sub>		Dead <sub>2015</sub>		
	2011	2013 2015		2011	2013	2015	$11 \rightarrow 13$	$13 \rightarrow 15$	$11 \rightarrow 13$	$13 \rightarrow 15$	
n(trees)	158	158	102	154	226	361	-	-	-	-	
eCROWN	779 (11)	744 (6)	672 (9)	749 (11)	729 (8)	723 (6)	-4	$^{-10}$	$^{-3}$	$^{-1}$	
eNEAS	653 (12)	639 (6)	571 (9)	591 (11)	598 (7)	595 (5)	-2	-11	1	$^{-1}$	
eTOTAL	934 (11)	1050 (6)	998 (8)	921 (11)	1001 (9)	1012 (6)	12	-5	9	1	
pA	83.5 (1.1)	82.1 (0.8)	74.5 (1.1)	77.5 (1.2)	77.6 (0.8)	76.0 (0.6)	-2	$^{-10}$	0	-3	
eUNDER	235 (4)	269 (3)	279 (4)	254 (5)	262 (4)	268 (3)	14	4	3	2	
eGND	185 (4)	388 (6)	356 (7)	181 (4)	356 (5)	334 (4)	110	-8	97	-6	
nCROWN, n	2.55 (0.02)	2.19 (0.02)	2.10 (0.02)	2.61 (0.03)	2.32 (0.02)	2.29 (0.02)	-14	-4	$^{-11}$	$^{-1}$	
nNEAS, n	1.70 (0.02)	1.56 (0.01)	1.51 (0.01)	1.63 (0.01)	1.56 (0.01)	1.56 (0.01)	-8	-3	-4	0	
FWHM, ns	6.72 (0.03)	6.87 (0.03)	6.80 (0.04)	6.54 (0.02)	6.72 (0.02)	6.78 (0.02)	2	$^{-1}$	3	1	
EQ50	0.379 (0.001)	0.385 (0.001)	0.390 (0.001)	0.384 (0.001)	0.387 (0.001)	0.387 (0.001)	2	1	1	0	
pDist, m	2.01 (0.01)	2.01 (0.01)	2.06 (0.02)	2.10 (0.01)	2.11 (0.01)	2.13 (0.01)	0	2	0	1	
lNEAS, ns	18.4 (0.24)	17.4 (0.15)	16.3 (0.20)	17.0 (0.23)	16.7 (0.13)	16.9 (0.11)	-5	-6	-2	1	
MinRelDist	0.51 (0.002)	0.44 (0.003)	0.44 (0.003)	0.50 (0.003)	0.44 (0.005)	0.44 (0.004)	$^{-12}$	0	$^{-12}$	0	
pARelDist	0.71 (0.004)	0.59 (0.004)	0.58 (0.005)	0.68 (0.006)	0.59 (0.008)	0.58 (0.005)	-17	-2	$^{-13}$	-2	
SZA	15.9 (0.1)	16.1 (0.1)	15.8 (0.2)	15.3 (0.2)	15.2 (0.2)	15.5 (0.2)					

# were < 3%.

# 3.3. Correlation of WF features over time, RQ4

Correlation of tree-level features was examined in three pairs: (1) Winter  $\times$  Early summer, (4) Winter  $\times$  Late summer, and (3) Early summer  $\times$  Late summer. In these combinations, the number of growing seasons between acquisitions was 1, 4 and 3. Fig. 15 shows the positive correlation of FWHM between the winter and late summer (case 4) in pine and spruce trees.

Table 13 shows the correlation coefficients by species and campaign combination. pADist displayed strong positive correlation in all species and acquisitions as the size of boreal 30–130-yr-old crowns does not change substantially in 1–4 years. In deciduous trees and evergreen conifers correlations were the strongest between leaf-on datasets (case 3) and the weakest between winter and late summer datasets (case 4), which were separated by four growing seasons. This can be expected as structural similarity of a tree decreases with time. The dead trees in Table 13 were dead in the first LIDAR campaign and their structure changed in the 45 months that followed. In dead trees, strength of average correlation was lower (0.53, 0.48) in cases 1 and 4 (2011  $\times$  2013, 2011  $\times$  2015) compared to case 3 (2013  $\times$  2015, r = 0.73). The

fine shoots had fallen in the first years following death and the structure remains more stable later on.

Correlation of energy features (eNEAS, eCROWN) was on average 0.34 between winter and summer (cases 1 and 4) in deciduous trees and 0.78 in evergreen conifers. Correlation was 0.59 in dead spruce. Among deciduous alder, birch and aspen, the correlation of FWHM between leaf-off and leaf-on data (cases 1, 4) was low, 0.15–0.50, whereas it was 0.69 and 0.82 in larch, which belongs to Pinaceae family together with pine and spruce. EQ50, which describes the shape of the NEAS showed negative correlation between leaf-on and leaf-off campaigns in deciduous trees.

#### 3.4. Correlation of WF features with tree height (age), RQ5

In pine and spruce, the correlations were assessed using both plot and tree-level features (Table 14), whereas only tree-level features were correlated with height in deciduous trees (Table 15).

The plot-level correlations in Table 14 are stronger compared to treelevel correlations because the plot mean values were computed using a large number of pulses per plot  $(700-1200 \text{ m}^2/\text{plot vs. } 3-100 \text{ m}^2/\text{tree})$ . Plot data shows that the proportion of pulses that displayed crown-only backscattering increased with stand height, while the correlation was



Fig. 8. Examples of tree crowns of different species. i) Leaf-on early summer birch and aspen, ii) leaf-off aspens, iii) old leaf-off birch, iv) recently died spruces, v) 80year-old spruces, vi) 90-year-old leaf-off larch, vii) 40-year-old leaf-on larches, viii) 20-year-old pine and ix)100-year-old pine.

negative for the proportion of pulses that displayed both crown and understory signals. The likely explanation for the negative correlation is that the understory trees in Hyytiälä are typically cleared in intermediate thinning operations.

In both pine and spruce, features pDist (average distance between WF peaks) and nCROWN (number of peaks) correlated strongly with canopy/crown height. High trees have longer and wider crowns, which increases the probability of pulses generating multiple return peaks. Variation in canopy height explained 65–71% of the plot-level variance of FWHM in pine plots and 38-49% in spruce plots. The correlation was positive, which means that the echoes of the older trees are 'harder' (FWHM, pA). This is also seen in Fig. 15. Correlation of EQ50 was negative, which means that echoes have a slower rise in young trees, especially in spruce. eNEAS, pA and eCROWN correlated positively with height in both conifers. Between-campaign differences in the correlation patterns are visible in eTOTAL, eNEAS (pine) and lNEAS (pine). eTOTAL increased with height in pine, whereas in spruce eTOTAL increased in the winter, but displayed a negative correlation with stand height in summer. The difference between pine and spruce can be explained in part by general differences of ground vegetation between young and old

stands (forest succession), but a more likely explanation is the weak backscattering in spruce stands (deep crowns), which remained below the sensor's WF storage threshold. When comparing the correlation patterns between plot and individual tree analyses, we can note differences that were likely caused by the different definition of crown base height between plot and tree-level data as well as the overall differences of the forests (all plots were in single-species forests).

In deciduous trees (Table 15), alder was left out because of limited age variation. In leaf-off state, eNEAS and pA correlated positively with height in aspen and larch, while correlations were weak in leaf-on data. In birch we observed the opposite as height correlated negatively with energy features in leaf-on data (r = -0.22-0.54) and no correlation was observed in leaf-off data. Echo width (FWHM) decreases with tree height in larch in all acquisitions (r = -0.61, -0.46, -0.44), but FWHM did not correlate strongly with height in aspen or birch. The positive correlation of nCROWN and pDist with height that was observed in conifers applies to deciduous trees as well. nNEAS, which is the number of peaks in the first NEAS, was not correlated with tree height in deciduous trees.



Fig. 9. Determination of the time of death for a spruce. The white line depicts the stem. Tree was alive in 2013 although parts of the crown were already defoliated. A neighboring birch was felled in February 2010. The images suggest that this tree grew 2.5 m in height in 10 years.



**Fig. 10.** Illustration of the capture of WF segments of an oblique pulse that intersects the crown. Points  $P_{enter}$ ,  $P_{exit}$  and  $P_{Ground}$  are 3D intersection points. Ground-pulse intersection was solved iteratively using a digital elevation model in one meter resolution.

# 3.5. Correlation of WF attributes with scan zenith angle, RQ4

We investigated the influence of SZA in pulse data of individual trees (Table 16). Alder was left out, because the samples were from two stands only. There were 52,000–195,000 pulses per species and campaign. The 95-% confidence intervals for the coefficients are approximately r  $\pm$  0.01. As expected, SZA was in very strong positive correlation with range. Similarly, SZA was in negative correlation with H<sub>rel</sub>, which is the relative height of point pA in the tree. This correlation means that as SZA increased, the first echoes were located higher in the tree, which can be explained by the occlusions caused by neighboring trees.

Overall, the correlations between SZA and WF features are weak, because of the high between-pulse variation. To exemplify, in pine, the correlation between eCROWN and height in tree-level data was 0.55 (late summer, Table 14), while it was only 0.16 in pulse data (not shown). Overall, SZA explained a small proportion of feature variance as  $R^2$  were mostly below 0.015 (-0.12 < r < 0.12). The largest effect was observed in dead standing spruce, in which nCROWN decreased with SZA with an  $R^2$  of 0.04–0.06 (-0.19 > r > -0.25). Vertical pulses yielded more peaks in dead spruce compared to oblique pulses, which is logical. The short and more 'diffuse' crowns of pines display much lower negative correlations for nCROWN. eCROWN was in weak positive correlation with SZA in spruce and showed negative correlation in larch and in leaf-on aspen. eNEAS (and pA) was in positive correlation with SZA in spruce and dead standing spruce and showed negative correlation in leaf-on aspen. The correlations imply that spruce returns are stronger in oblique pulses, while the opposite is true in leaf-on aspen. eCROWN of leaf-off aspen did not correlate with SZA. Leaf-off and leafon correlations of eCROWN, eNEAS, pA and nCROWN differed also in birch.

Negative correlation of both pARelDist and pADist with SZA implies that oblique pulses penetrated deeper into the crowns. eTOTAL was not systematically correlated with SZA. eGND however showed a systematic negative correlation, which means that oblique pulses display lower eGND, which could be due to larger transmission losses of the oblique pulses that travel a longer path inside the forest.

# 4. Discussion and conclusions

# 4.1. Major findings regarding research questions 1-5

RQ1. Using non-tree targets, we confirmed that there were no systematic differences between the acquisitions. The sensor had functioned

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**Fig. 11.** Frequency distributions of first-return heights in two 40-yr-old birch plots, in two spruce (40- and 120-yr-old) plots and in two pine (50- and 90-yr-old) plots. Birch plots have a dense 1–5-m-high understory of spruce and the drained bog has public birch in the understory. The percentages are the proportions of pulses echoing from below 2 m, i.e. pulse penetration.



Fig. 12. WF of a 90-yr-old pine. Graph illustrates the three WF segments and their WF attributes. WF<sub>Crown</sub> has two peaks (nCROWN = 2) and the first peak (point pA) is 19 m (~130 ns) above the ground. The first-return NEAS has a single peak (nNEAS = 1, pA = 25, INEAS = 7) with an echo width (FWHM) of 5.3 ns. The value of EQ50 ('center of gravity') is close to 0.5, because the first NEAS is quite symmetric. The distance between peaks in WF<sub>Crown</sub> (pDist) is 5.1 m. Crown energy (eCROWN) was contributed by two canopy echoes. The pulse likely intersected a stem near the ground (eUNDER = 170) and gave rise to a ground signal as well (eGND = 225). The WF consisted of two 80-sample-long sequences separated by a 25-ns pause in WF storage.

similarly, and range-normalization removed the signal variations such that the relative match of signal levels between campaigns was below 5% in extended targets. We observed a substantial specular component in old asphalt at SZA above 20° when evaluating the radiometric match. We could not find studies, where the same was reported using a calibrated airborne sensor. Our experience shows that it is important to consider directional effects in selecting the radiometric control targets. Trees that had died recently displayed also marginal differences in signal levels (Table 12), but we cannot recommend their use as multitemporal radiometric control targets.

RQ2. In deciduous trees, aspen, alder, larch and birch, the influence of phenology was substantial when contrasting leaf-off and leaf-on WFs.

Comparison of early and late summer data displayed less pronounced effects, but there were some between-species differences. In needleleaf larch, the high reflectance of the bark made it different from the other deciduous species in winter LiDAR. The average crown signals in larch were nearly at the same level as in summer, while backscattering in other deciduous species was very low in the winter. Leaf-off larch actually gave rise to the strongest individual WFs in all datasets although very few pulses produced a single echo in leaf-off larch (Fig. 13). Leaf-off echoes were 4–14% wider compared to leaf-on data in broadleaved trees except for aspen, in which echo width did not vary between winter, early and late summer. The vertical branches and erectophile leaves of aspen explain the irregularity. In aspen, canopy signals also 'increased during



Fig. 13. Joint distributions of attributes eGND and eCROWN in pulses from a 40-year-old larch stand. Larch is a deciduous conifer.

the summer', which was most likely due to the delayed development of leaves during the early summer LiDAR acquisition.

Evergreen conifers pine and spruce displayed only minor differences between acquisitions except for crown energy (eCROWN, eNEAS) and peak amplitude (pA), which varied 4–9-% between acquisitions. Crown backscattering in spruce was the strongest in winter and the lowest in late summer, whereas in pine the signals were the strongest in early summer and the winter signal levels did not deviate from late summer despite the 20–30-% increase of needle mass, which decreases the gap

fraction during the summer (Lang et al., 2017). The relatively low winter backscattering in pine calls for an explanation, and we cannot rule out that the pine shoots were moist, when it was not observed in spruce. Nor can we rule out that pine stamens increased the backscatter reflectance of the early summer crowns and caused 'an early summer peak'. Relative to spruce, we could argue that the 1550-nm backscattering in pine decreases during the summer. In 1064-nm LiDAR, Hovi et al. (2016) observed the opposite. Differences in needle clumping between winter and early summer could explain the signal differences in pine, but we did not find research that would show that pine shoots have lower silhouette area in the winter. Water content of wintering needles is lower compared to summer, but this would cause an opposite phenomenon in pine (stronger winter signals). In spruce, the signals also decreased during the summer despite a 10-15-% increase of needle mass. Signal decrease during the summer in both pine and spruce could also be explained by the decrease of the visible bark silhouette as bark has a higher 1550-nm reflectance compared to needles.

RQ3. Inclusion of dead standing spruce in the experiments was partly motivated by their use as radiometric control targets. Only during the data analyses did we realize that the structure of dead standing spruce changes over time and we interpreted their history using historic aerial images. Our results imply that WF features of dead spruce change due to 'aging' as the needles and small branches fall down in the first years following death. Further research is needed to verify the rate at which WF features change and if the phenomena depend for example on tree age (size) and species. When we contrasted WF features of the three campaigns in dead spruces, such that the influence of 'aging' was minimized, the WF features showed only small differences (<3%) in energy and pA and these small differences did not match the 'phenological patterns' observed in living pine or spruce.

RQ4. As expected, the tree-level mean WF features correlated over time and the correlation was the weakest, when contrasting LIDAR data, which had the longest temporal lag. Feature correlation measures a 'tree



Fig. 14. Relative frequency distributions of eCROWN, eGND and eTOTAL in the 15 plots of the 90-year-old Lapinkangas pine forest. Black = winter, Red = early summer, Green = late summer. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



Fig. 15. Correlation of FWHM between winter and late summer data in spruce and pine individuals of plots OG (x) and IM (o).

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# Table 13

Between-campaign correlation coefficients of tree-level mean features in deciduous trees and dead spruce. 1 = winter 2011 x early summer 2013, 4 = winter 2011 x late summer 2015, 3 = early summer 2013 x late summer 2015. The correlation in dead spruce was computed in trees which were dead in the first LiDAR and were standing trees in later campaigns. Colors denote sign and strength of correlation.

	Pine, n=605		Spruce, n=809		Birch, n=568			Alder, n=148			Aspen, n=167			Larch, n=336			Dead spruce, n=158				
	1	4	3	1	4	3	1	4	3	1	4	3	1	4	3	1	4	3	1	4	3
eCROWN	0.80	0.77	0.86	0.76	0.74	0.87	0.34	0.23	0.71	0.41	0.14	0.41	0.50	0.40	0.47	0.24	0.01	0.35	0.60	0.38	0.68
nCROWN	0.85	0.73	0.81	0.84	0.78	0.83	0.62	0.57	0.69	0.57	0.23	0.53	0.71	0.40	0.57	0.68	0.40	0.51	0.17	0.30	0.72
eNEAS	0.75	0.72	0.83	0.68	0.69	0.84	0.29	0.23	0.71	0.38	0.18	0.42	0.36	0.31	0.52	0.13	-0.05	0.43	0.62	0.51	0.74
pА	0.85	0.85	0.91	0.74	0.74	0.87	0.08	0.15	0.62	0.11	0.09	0.45	0.25	0.24	0.54	0.32	0.40	0.60	0.64	0.60	0.73
INEAS	0.75	0.73	0.82	0.69	0.66	0.78	0.51	0.43	0.67	0.65	0.24	0.41	0.64	0.42	0.60	0.65	0.29	0.58	0.51	0.44	0.75
nNEAS	0.74	0.68	0.80	0.58	0.54	0.63	0.41	0.40	0.63	0.54	0.24	0.40	0.63	0.35	0.52	0.55	0.24	0.51	0.29	0.24	0.65
FWHM	0.81	0.76	0.79	0.71	0.62	0.72	0.37	0.43	0.65	0.40	0.15	0.35	0.50	0.31	0.69	0.82	0.68	0.72	0.49	0.49	0.73
EQ50	0.52	0.49	0.58	0.35	0.27	0.46	0.08	0.09	0.54	-0.12	0.07	0.46	-0.33	-0.27	0.38	-0.32	0.04	0.44	0.61	0.57	0.68
pDist	0.84	0.82	0.82	0.83	0.81	0.83	0.66	0.54	0.56	0.60	0.26	0.42	0.72	0.29	0.39	0.82	0.43	0.50	0.54	0.59	0.73
MinRelDist	0.80	0.70	0.74	0.79	0.69	0.73	0.44	0.28	0.51	0.24	0.07	0.47	0.38	0.15	0.27	0.34	0.10	0.43	0.40	0.46	0.85
pARelDist	0.79	0.58	0.74	0.86	0.77	0.84	0.45	0.38	0.70	0.40	0.09	0.40	0.63	0.36	0.58	0.56	-0.03	0.41	0.59	0.58	0.86
pADist	0.97	0.95	0.96	0.98	0.95	0.95	0.92	0.89	0.94	0.88	0.71	0.85	0.97	0.95	0.98	0.95	0.88	0.91	0.86	0.85	0.95
eUNDER	0.64	0.59	0.71	0.66	0.63	0.62	0.44	0.34	0.64	0.24	0.02	0.21	-0.06	0.02	0.30	0.16	0.19	0.44	0.64	0.57	0.62
eGND	0.48	0.41	0.73	0.42	0.47	0.62	0.48	0.18	0.52	0.54	0.52	0.60	0.13	0.00	0.34	0.70	0.21	0.41	0.52	0.54	0.72
eTOTAL	0.44	0.52	0.81	0.64	0.66	0.80	0.29	0.10	0.75	0.18	0.22	0.56	0.06	0.06	0.45	0.02	-0.08	0.31	0.51	0.29	0.62
Average	0.74	0.69	0.80	0.70	0.67	0.76	0.42	0.35	0.66	0.42	0.22	0.46	0.46	0.30	0.51	0.48	0.27	0.50	0.53	0.49	0.74

# Table 14

Correlation coefficients between canopy/tree height and WF attributes in pine and spruce. In plot data, the correlations are given also for pulse proportions (P). 'Crown only' refers to pulses that did not display ground (gnd) or understory (under) backscattering. P(h < 2 m) is the proportion of first-returns below 2 m, i.e. 'pulse penetration', which measures canopy closure.'P, crown + gnd, %' is the proportion of pulses that displayed both crown and ground signals. Wi, ES and LS refer to winter, early and late summer LiDAR data, respectively. Colors denote sign and strength of correlation.

	Pine	ə, n=47 p	olots	Spruc	e, n=40	plots	Pine	, n=605	trees	Spruce, n=809 trees			
Plot/tree average	Wi	ES	LS	Wi	ES	LS	Wi	ES	LS	Wi	ES	LS	
P(h<2m), all pulses, %	-0.33	-0.16	-0.11	-0.02	-0.19	-0.23	-	-	-	-	-	-	
P, crown only, %	0.84	0.90	0.90	0.91	0.87	0.81	-	-	-	-	-	-	
P, crown + gnd, %	-0.03	0.17	-0.01	-0.18	-0.24	-0.39	-	-	-	-	-	-	
P, crown + under, %	-0.82	-0.86	-0.83	-0.83	-0.69	-0.65	-	-	-	-	-	-	
P, crown + under + gnd, %	-0.36	-0.37	-0.26	-0.03	0.41	0.48	-	-	-	-	-	-	
eTOTAL	0.76	0.54	0.51	0.28	-0.34	-0.34	0.57	0.21	0.30	0.31	-0.04	-0.11	
eCROWN, crown-only	0.79	0.74	0.71	0.23	0.19	0.21	0.7	0.63	0.62	0.35	0.33	0.36	
eCROWN	0.8	0.71	0.71	0.58	0.59	0.64	0.64	0.55	0.55	0.44	0.46	0.44	
eNEAS	0.69	0.38	0.34	0.40	0.37	0.41	0.52	0.42	0.43	0.24	0.17	0.16	
eUNDER	0.83	0.80	0.77	0.87	0.84	0.83	0.27	0.29	0.31	0.45	0.44	0.51	
eGND	0.43	0.32	0.28	0.17	-0.23	-0.32	0.06	-0.16	-0.03	0.13	-0.14	-0.04	
nCROWN	0.87	0.84	0.79	0.70	0.57	0.49	0.44	0.28	0.32	0.61	0.63	0.63	
pDist, m	0.92	0.92	0.92	0.78	0.81	0.8	0.76	0.73	0.66	0.59	0.63	0.63	
рА	0.8	0.73	0.69	0.48	0.54	0.48	0.64	0.58	0.65	0.44	0.41	0.39	
FWHM, ns	-0.84	-0.83	-0.81	-0.7	-0.68	-0.62	-0.54	-0.52	-0.54	-0.47	-0.47	-0.44	
INEAS, ns	0.04	-0.52	-0.45	-0.06	-0.16	-0.09	-0.21	-0.39	-0.43	-0.14	-0.24	-0.25	
EQ50	-0.49	-0.24	-0.29	-0.53	-0.42	-0.42	-0.18	-0.06	0.03	-0.09	0.04	0.12	

effect', i.e. something unique in the tree individual as indicated by a feature. Tree effect is strong in passive image data, especially in nearinfrared signals (Korpela et al., 2014) and was quantified in 1064-nm WF data by Hovi et al. (2016). Our results showed that feature correlation was much stronger in conifers compared to deciduous trees in which leaf-off and leaf-on features correlated poorly with the exception of (needleleaf) larch, in which some of the geometric features showed very high correlation even between leaf-off and leaf-on data. In evergreen conifers, we contrasted old trees (plot OG) with 50-year-old trees (plot IM), which differ in height growth and therefore in shoot/crown structure. The feature correlation was slightly stronger in the old trees (results were left out). RQ5. Analyzing the correlation of scan zenith angle (SZA) and tree height on WF features was considered important as previous research has shown that they influence 1064-nm WFs in pine, spruce and birch (Hovi et al., 2016). Correlation with height explains also the considerable stand effect observed in Hovi et al. (2016). Differences in the influence of SZA and height between phenostates has also implications for species classification applications. In Hyytiälä, the height of dominant trees correlates positively with stand age owing to the thin-from-below thinning rule and thus the results concerning height apply to age as well. SZA and range were in strong positive correlation as the flying height was kept fixed and there was only moderate topographic variation. SZA was in weak positive correlation with eNEAS and pA in pine and dead

Correlation coefficients between mean WF features and tree height in deciduous trees. Wi, ES and LS refer to
winter, early and late summer, respectively. Colors denote sign and strength of correlation.

	Birch	, n=568	trees	Asper	n, n=167	trees	Larch, n=336 trees				
Feature	Wi	ES	LS	Wi	ES	LS	Wi	ES	LS		
eTOTAL	0.16	-0.21	-0.25	0.51	0.12	0.15	0.73	0.07	0.03		
eCROWN_only	0.19	-0.42	-0.33	0.40	0.01	0.13	0.37	0.28	0.12		
eCROWN	-0.10	-0.31	-0.33	0.36	0.02	0.08	0.62	-0.19	-0.16		
eNEAS	0.06	-0.54	-0.42	0.17	-0.09	-0.18	0.57	0.14	-0.20		
рА	0.00	-0.22	-0.29	0.44	0.02	0.10	0.72	0.11	0.19		
eUNDER	0.24	0.06	0.01	-0.04	-0.15	0.02	-0.11	-0.02	-0.09		
eGND	-0.06	-0.13	-0.02	-0.11	0.04	-0.11	0.50	0.31	-0.02		
nCROWN	0.45	0.30	0.31	0.65	0.57	0.33	0.59	0.61	0.29		
nNEAS	-0.15	-0.15	-0.12	0.27	0.14	0.00	0.13	-0.08	-0.22		
FWHM	-0.13	-0.13	-0.09	-0.09	-0.07	-0.05	-0.61	-0.46	-0.44		
EQ50	-0.12	0.14	0.06	0.23	-0.13	-0.23	-0.51	0.19	0.06		
pDist	0.61	0.48	0.38	0.66	0.61	0.37	0.62	0.68	0.58		
INEAS	-0.17	-0.24	-0.21	0.25	0.08	0.01	0.11	-0.31	-0.33		

#### Table 16

Correlation coefficients between WF attributes and SZA in pulses intersecting individual trees.  $H_{rel}$  is the relative height of point pA in the tree (0.45–1). Range is the distance between the sensor and point pA (740–850 m). Wi, ES and LS refer to the winter, early summer and late summer, respectively. Colors denote sign and strength of correlation.

	Pine			Spruce			D	Dead Spruce			Birch			Aspen			Larch		
	Wi	ES	LS	Wi	ES	LS	Wi	ES	LS	Wi	ES	LS	Wi	ES	LS	Wi	ES	LS	
eTOTAL	0.08	-0.03	-0.07	0.10	-0.01	-0.01	-0.03	-0.06	-0.17	0.05	-0.07	-0.05	-0.02	-0.07	-0.11	-0.09	-0.08	-0.05	
eCROWN	0.04	0.00	-0.02	0.08	0.03	0.01	-0.03	-0.01	-0.08	0.01	-0.03	-0.04	-0.01	-0.08	-0.12	-0.07	-0.06	-0.03	
eNEAS	0.06	0.02	0.00	0.13	0.08	0.08	0.06	0.11	0.04	0.05	0.00	0.01	0.05	-0.02	-0.05	0.00	0.01	-0.01	
pА	0.03	-0.02	-0.08	0.11	0.05	0.04	0.07	0.13	0.05	0.08	-0.01	-0.02	0.05	-0.04	-0.06	0.02	0.00	0.03	
eUNDER	0.10	0.13	0.04	0.09	0.09	0.05	0.03	0.04	0.01	0.15	0.04	0.02	0.07	0.04	0.07	0.01	0.07	0.05	
eGND	-0.08	-0.05	-0.08	-0.02	-0.08	-0.09	-0.05	-0.09	-0.10	-0.05	-0.06	-0.03	-0.10	-0.05	-0.06	-0.05	-0.09	-0.06	
nCROWN	-0.05	-0.04	-0.05	-0.10	-0.09	-0.13	-0.19	-0.25	-0.21	-0.13	-0.05	-0.08	-0.02	-0.03	-0.05	-0.13	-0.09	-0.06	
nNEAS	0.01	-0.01	0.04	0.04	0.03	0.04	0.01	-0.01	-0.03	-0.01	0.01	0.02	0.02	0.01	0.00	-0.05	-0.02	-0.04	
FWHM	0.05	0.06	0.10	0.04	0.05	0.06	0.05	0.06	0.05	-0.04	0.02	0.03	0.01	0.02	0.01	0.03	0.04	-0.03	
pDISt	-0.03	0.00	-0.08	-0.11	-0.13	-0.14	-0.12	-0.16	-0.11	-0.08	-0.05	-0.07	-0.06	-0.05	-0.06	-0.05	-0.02	0.00	
INEAS	0.04	0.02	0.07	0.10	0.06	0.10	0.04	0.05	0.01	0.01	0.02	0.04	0.05	0.02	-0.01	-0.02	0.01	-0.04	
EQ50	-0.01	0.00	0.00	-0.05	-0.03	-0.04	-0.03	-0.04	-0.02	0.03	-0.02	-0.02	0.01	0.00	0.00	0.01	-0.03	-0.01	
MinrelDist	-0.13	-0.11	-0.11	-0.14	-0.13	-0.12	-0.14	-0.14	-0.14	-0.15	-0.11	-0.12	-0.13	-0.11	-0.09	-0.14	-0.12	-0.12	
pADist	-0.05	-0.08	-0.09	-0.05	-0.09	-0.09	-0.11	-0.11	-0.10	-0.10	-0.05	-0.07	-0.07	-0.06	-0.06	-0.11	-0.06	0.01	
pARelDist	-0.10	-0.11	-0.13	-0.13	-0.16	-0.16	-0.17	-0.18	-0.15	-0.13	-0.05	-0.11	-0.08	-0.07	-0.08	-0.15	-0.12	-0.17	
Hrel	-0.09	-0.09	-0.10	-0.11	-0.10	-0.10	-0.09	-0.09	-0.08	-0.08	-0.09	-0.10	-0.07	-0.09	-0.10	-0.12	-0.09	-0.10	
range	0.90	0.82	0.91	0.92	0.82	0.89	0.94	0.82	0.92	0.89	0.82	0.90	0.86	0.81	0.91	0.85	0.82	0.84	

spruce but showed no correlation in other species. SZA was in weak negative correlation with pARelDist feature, which implies that oblique pulses penetrated deeper into the crowns, which is logical. Height correlated positively with crown backscattering in pine and spruce and the correlation was negative in leaf-on birch. These findings are in line with Hovi et al. (2016) in 1064-nm data. In larch, tree height correlated strongly with eNEAS, eCROWN and pA, but only in leaf-off data. The thicker branches of older larches may explain the effect. The reflective bark in the larch branches was visible to the LiDAR in winter but not in leaf-on data. Height was in negative correlation with FWHM in all species and strongest correlation was observed in conifers pine, spruce and larch. Older trees comprise thus 'harder' LiDAR targets, which was also observed by Hovi et al. (2016) in 1064-nm data.

Other interesting findings include the 'phenology' of eGND, which is the ground energy in pulses that displayed crown backscattering. Winter eGND was in most cases 40–60% lower compared to summer owing to the wet ground. We conclude that eGND is influenced by canopy transmission losses, which also depend on the tree species and cannot be deduced from canopy backscattering unless the tree species is known as shown in Fig. 13. The ground flora and its moisture in the winter data was probably also influenced by the species that formed the tree layer. Phenology of ground flora should be examined using pulses that are free from transmission losses (Korpela, 2008), but we excluded it except in the sparse Lapinkangas pine forest, where we contrasted changes of eGND between pulses that did not intersect with trees to pulses that displayed canopy scattering.

# 4.2. Confines of the study

This experimental study was based on observations collected in leafoff (November) and in leaf-on (June and August) conditions. LiDAR data were collected for several purposes (Korpela et al., 2013, 2020, 2023) and the acquisitions were separated by one and three growing seasons. During this time trees grew in height, crown width and crown base height and some trees died, were felled or broke. Then again, the temporal lag made it possible to observe how structural changes in dead standing trees influence WF features.

While we had observations of seven species classes, we did not have trees younger than 20 years and black alder was found in two stands only. Trees did not represent the full structural variation found in southern Finland, but in terms of phenology this should not pose a problem. Total number of plots was 102 (11.5 ha). Finding pure canopies of pine, spruce and birch was laborious, because we did not allow any species mixture and large plots (0.07–0.12 ha) assured reliable plotlevel estimates.

We were able to show that the relative match of the repeated LiDAR datasets was good, and hence the findings regarding even subtle changes during the summer are relevant. Placing large reflectance calibration targets such as reflectance tarps across the inventory area would have been optimal. Instead of temporary targets, we used road surfaces, sand pits, powerline cables and roof structures that were found in the study area. The sun-photometer observations unfortunately did not cover the winter acquisition as the sensor had been dismantled for winter.

In range-normalization, we carried out a correction for quadratic losses and assumed that amplitude data represent ratio-scale (unitless) measurements of instantaneous at-sensor radiance. Only a small offset term was subtracted. Because SZA was strongly correlated with range, and because we did not know the directional reflectance properties of the used reference surfaces, we could only conclude that the normalization removed most SZA effects in all other targets except for asphalt, which displayed a clear specular component at SZA >20°. Range normalization can introduce substantial bias (as a function of target reflectance), if the assumptions regarding receiver response are not true (Korpela et al., 2010b).

Our field observations indicated that birch was in full leaf in May 28, 2013, whereas aspen leaves were not entirely developed in parts of the area. Because the isolated aspens were scattered across the 1000-ha area, we could not visit all of them and missed some of the phenological variation. Nor could we observe the spatial variation in the flowering of pine, which was at its peak during the early summer campaign.

Estimates of crown base height (CBH) and terrain elevation were needed when splitting the WFs between the crown, understory and ground components. In tree-level analyses, we had to assume a fixed crown ratio. CBH determines the split of the WFs between crown and understory, whereas the NEAS attributes (pA, nNEAS, eNEAS and FWHM) are less influenced by crown depth. Estimation of CBH in LiDAR data is possible (Vauhkonen, 2010), but is prone to substantial errors. Because of the ringing in receiver of LMS-Q680i, we had to apply a threshold not to analyze noise. It would have been beneficial if there had not been pauses in WF storage when backscattering dimmed, because continuous WFs display better the weak scattering (and hence transmission losses) as shown in Korpela (2017).

# 4.3. Future perspectives

Based on our findings in pine, we suggest research in the geometry of needle angles and shoot orientation in pine at temperatures below zero as clumping is an important parameter in radiative transfer models (Yan et al., 2021). Similarly, we suggest that the influence of early summer 'flowering' by pine stamens is investigated further using for example UAV-based LiDAR remote sensing or by using static sensors that are placed above the canopy.

The footprint size that we investigated was 35–40 cm. WF features are influenced by beam divergence as shown in an observational study by Korpela (2017), who compared footprint diameters 11, 22, 40 and 59 cm in 1064-nm data. It is likely that the phenological patterns will exhibit variation when the scale changes as the canopy gap size distribution depends on the species. The wavelength will also exercise an effect as the relative differences of bark and foliage reflectance vary between species (Rautiainen et al., 2018). Hence more studies using

accurate simulators or experimental data are needed. The use of UAVbased systems or permanently installed laser scanners may help the experimenters.

Based on our findings in dead spruce, we propose further research that explores how tree age and the 'aging' of dead standing trees influences WF features as these changes must be accounted for in the detection and species identification of dead standing trees.

# 4.4. Conclusions

Leaf-off deciduous trees did not display similar patterns of WF feature changes due to phenology, but the patterns were influenced by between-species differences of bark reflectance, branching pattern and leaf-orientation. This opens up possibilities for enhanced tree species identification in WF data using even the combination of leaf-off and leaf-on data. The 'echo width anomaly' in aspen, high 1550-nm reflectance of dead standing spruce, high winter reflectance of larch and low leaf-off signals in birch comprise features that may prove useful. However, the separation of pine and spruce in 1550-nm data may pose issues if that wavelength is used. Aspen is an ecologically important species, and the monitoring of tree mortality constitutes a topical issue. However, we only studied dead spruce and more research is needed in other important species.

We showed that even subtle geometric-optical changes in vegetation can be observed if the (WF) LiDAR acquisitions are repeated in appropriate weather, and by using the same trajectories and sensor settings. The response of the sensor has to be known so that range-normalization successfully removes the effects by spherical losses that are substantial in LiDAR remote sensing. Phenology was found to influence WFs, even when contrasting early and late summer acquisitions. Especially regarding species identification using WF features, it is important that LiDAR data acquisition is not initiated until the 'late species', such as aspen in our study area, have reached full leaf.

#### Credit author statement

IK arranged the experiment and field data, coded the photogrammetric and LiDAR tools. IK measured the crown models and reference trees by visual interpretation and wrote the first version of the manuscript. AP coded parallel WF processing tools to narrow down the risk of implementation errors and participated in the planning of the analyses. AH wrote the code that combined the trajectory data, discrete returns and WF samples and quantified the effects by ringing. All authors participated in the writing of the final manuscript.

# **Declaration of Competing Interest**

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Ilkka Korpela reports financial support was provided by Academy of Finland. Aarne Hovi reports financial support was provided by European Research Council. Samuli Junttila reports financial support was provided by Academy of Finland.

# Data availability

Data will be made available on request.

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