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Can models for forest attributes based on airborne laser scanning be generalized for different silvicultural management systems?

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ABSTRACT

In Finland, interest in continuous cover forestry (CCF) has increased rapidly in recent years. During those years CCF has been examined from various viewpoints but not from the perspective of forest inventories. This holds especially true for applications based on remote sensing. Conversely, airborne laser scanning (ALS) data have been widely used to predict forest characteristics such as size distribution and vertical forest structure, which are closely related to the forest information needs of CCF.

In this study we used the area-based approach to predict a set of stand attributes from ALS data (5 pulses per m^2) in a CCF forest management experiment in Katajamäki, eastern Finland. In addition to the CCF stands, the experiment included shelterwood stands and untreated stands. The predicted attributes included volume, biomass, basal area, number of stems, mean diameter, Lorey's height, dominant height, standing dead wood volume, parameters of the theoretical stem diameter distribution model, understory height and number of understory stems. Our main aim was to test whether the same model could be used across different management systems. The accuracy of the attributes predicted for the CCF stands was compared with the predictions for the other management systems in the same experiment. We also compared and discussed our results in relation to the even-aged stand attribute predictions that were conducted by using separate operational forest data collected from sites surrounding Katajamäki.

The results showed that forest data from the different management systems could be combined into a single model of a stand attribute, i.e., ALS metrics were found to be suitable for comparing different management systems in regard to differences in forest structure. The accuracy of the predicted attributes in the CCF plots was comparable to that of the other management alternatives in the experiment. The accuracy was also comparable to that of even-aged forests.

The results of this study were promising; the stand attributes of CCF-managed forests could be predicted analogously to those of other management systems. This indicates that for the purposes of forest inventories there may not be a need to stratify forest lands by management system. It should be noted, however, that the study area was relatively small, that the forest stands were harvested in the 1980 s, and that the attributes may not have been completely exhaustive for CCF.

1. Introduction

Continuous cover forestry (CCF) has traditionally been practiced in many regions, i.e., Central Europe (Sterba 2004). There are several terms and variants associated with CCF management systems, such as (*i*) repeated high thinning combined with natural regeneration, (*ii*) use of gap felling with a naturally emerging understory providing new tree generation, and (*iii*) traditional selection felling, i.e., uneven-aged management, which has been used historically in Central Europe. There is also a long history of CCF-type management in Finland, where it has been applied in forests where a continuous tree cover is especially needed for preservation and protection of vulnerable species,

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management of the landscape or maintenance of recreational or landscape values. However, this method became illegal in the late 1940 s due to the potential for forest degradation (Sarvas 1944, Leikola 1986a, b). In the subsequent 60-year period, even-aged rotation forestry was the dominant practice in Finnish forest management. It entailed even rotation lengths with consecutively implemented harvestings, where forests were thinned from below and where regeneration occurred when the forests were clear-felled at the end of the rotation. In the past 20 years, however, interest in CCF has increased again for a variety of reasons.

One reason for the increased interest in CCF is the need to implement forest management procedures that do not entail clear-felling. According to Valkeapää et al. (2009), only 5% of Finns accept clear-felling without any reservations. According to Kumela and Hänninen (2011), 12% of forest owners want to use CCF in all their forests, 15% in some forests, 25% may try it, 28% want to know more about the method, and only 10% will never use it. Other reasons for the increased popularity of CCF management include its potential economic profitability (Tahvonen et al. 2010, Pukkala et al. 2010) and the fact that the relative importance of non-timber benefits of forests is increasingly acknowledged. Similar trends have also been found in other countries (e.g., Sweden; Axelsson and Angelstam 2011). Special attention has also been paid to the carbon sequestration function of forests where uneven-aged management and other forms of CCF have produced a slightly better carbon balance in the short term than even-aged plantation forest stands (Pukkala et al. 2010). This is due to the better assortment distribution of harvested timber in CCF than in even-aged forestry. Sawnwood-sized harvested timber in CCF improves the possibilities for the establishment of long-term carbon stores in wood products, for example.

In Finland, CCF has been examined from a number of viewpoints. Early studies, such as Sarvas (1944), studied the effect of selective cutting of logs in privately owned forests in southern Finland. A new era in CCF research started around the 1980–90 s with the establishment of new permanent-plot-based field experiments (Pukkala et al. 2011). These experiments included both a network of uneven-aged management plots (ERIKA) (Saksa 2004) and separate experiments such as the one in Katajamäki, which is used in this article. These experiments provided results on a range of topics that included forest growth and yield (Lähde et al. 2002, Hynynen et al. 2019, Bianchi et al. 2020), ingrowth and early development of seedlings (Eerikäinen et al. 2007, Eerikäinen et al. 2014, Kuusinen et al. 2019), forest damage (Komonen et al. 2020, Valkonen et al. 2020), logistics (Sirén et al. 2015), wood quality (Pyörälä et al. 2022) and forest planning and the carbon balance (Shanin et al. 2016). Similar trends of increased CCF research can also be found in Sweden (Lundqvist 1993, 2017).

Although CCF has been studied in Finland extensively, it has not yet been studied from the forest inventory viewpoint. Comprehensive solutions for a CCF inventory based on airborne laser scanning (ALS) have also been lacking internationally (Köhl and Baldauf 2011). It is clear that forest attributes, such as volume and biomass, are also of major interest in a CCF inventory. For CCF management planning, however, it is necessary to know the number, size and species distribution of the small-sized understory trees that grow under the dominant tree canopy, for the management relies heavily on the cohorts of non-dominant trees. The National Forest Inventory results show that though the understory is very common in Finnish forests, that does not mean that CCF management is predominant; in fact, <10,000 ha are classified as uneven-aged managed (Korhonen et al. 2021).

ALS data have been used in numerous studies that focused on key characteristics of CCF. For instance, data have been used to describe the vertical structure of forests from an ecological point of view, for the detection of canopy gaps, and for the prediction of canopy coverage (Vepakomma et al. 2008, Korhonen et al. 2011, Dalagnol et al. 2021). In addition, methods have been developed to quantify the vertical forest structure for biodiversity or other assessments (Zimble et al. 2003, Maltamo et al. 2005, Hill and Broughton 2009, Morsdorf et al. 2010, Hamraz et al. 2017, Crespo-Peremarch et al., 2018), to characterize forest fuels (Riano et al. 2003, Maltamo et al. 2020), to classify canopy layers (Martinuzzi et al. 2009, Miura and Jones 2010, Wilkes et al. 2016, Adnan et al. 2019), and to find regeneration patterns (Bollandsås et al. 2008). However, most of these studies have not been conducted in CCF-managed forest areas. In some studies the study area has comprised uneven-aged forests (Bollandsås and Næsset 2007, Bollandsås et al. 2008, Spriggs et al. 2015, Stefanidou et al. 2020, Leclère et al. 2022). In most of these studies, the stem diameter distribution has been considered. For example, Valbuena et al. (2013) reported that the Gini coefficient based on tree diameters could be used to separate uneven-sized from even-sized forests. However, these studies do not compare the errors associated with the inventory outputs across CCF systems with other forest management systems. Instead, the study areas appear to be continuously managed with the uneven-aged forestry approach.

In the current study, our aim was to test whether the same ALS-based forest attribute models could be used across different management systems. We predicted the stand attributes of a prior CCF forest management experiment by applying the area-based approach (ABA) with ALS data. The experiment also included shelterwood stands and untreated stands. The predicted stand characteristics were timber volume, biomass, basal area, number of stems, mean diameter, Lorey's height, dominant height, standing dead wood volume, parameters of the theoretical stem diameter distribution model, understory height, and number of understory stems. The accuracies of the predicted attributes were compared across management systems within the same experiment. By applying separate data, we also compared and discussed our results in relation to the attributes predicted for even-aged stands.

2. Material and methods

2.1. Study area and field measurements

The study area is an experimental area for forest management that was established in 1985. Located in Katajamäki, Rautavaara, Finland (N 63°71′, E 28° 32′) the forests within the experimental area represent coniferous-dominated boreal forests. The area is dominated by Norway spruce (*Picea abies* (L.) Karst, proportion with respect to the total volume: 61.3%) with an admixture of Scots pine (*Pinus sylvestris* L., 27.2%) and birch (*Betula* spp. 11.5%). The experiment included forest stands with seven different treatments (Leikola 1986a, b):

i) Shelterwood dominated by Norway spruce;
ii) Shelterwood dominated by Scots pine;
iii) Shelterwood dominated by Norway spruce, Scots pine and birch;
iv) Uneven-aged management;
v) Selective cutting;
vi) Small-scale clearcutting, and
vii) Untreated (no management).

In this study, treatments i–iii were merged to form shelterwood stands, iv–vi were CCF stands, and vii represented untreated stands. In this report, the management systems or treatments examined are referred to as 1) shelterwood, 2) CCF, and 3) untreated stands. All treatments were repeated four times (Fig. 1).

We established new circular plots (15 m radius) in the experimental stands in summer 2021. In each of the CCF and shelterwood stands, one plot was established, but in one of the CCF stands and all of the untreated stands, two plots were established. The plots were accurately positioned by means of a global navigation satellite system (GNSS) with an external antenna elevated to 5 m, and the positions were post-corrected afterwards by means of a differential GNSS algorithm and reference positions. The measurements taken included the diameter at breast height (DBH) and the height of each tree with a DBH > 5 cm. We also registered the tree species and the existence of an understory (density of trees with DBH < 5 cm). We then calculated the tree volume (V, m^3 ha^{-1}) and the above-ground biomass (AGB, Mg ha^{-1}) by using the tree diameter and

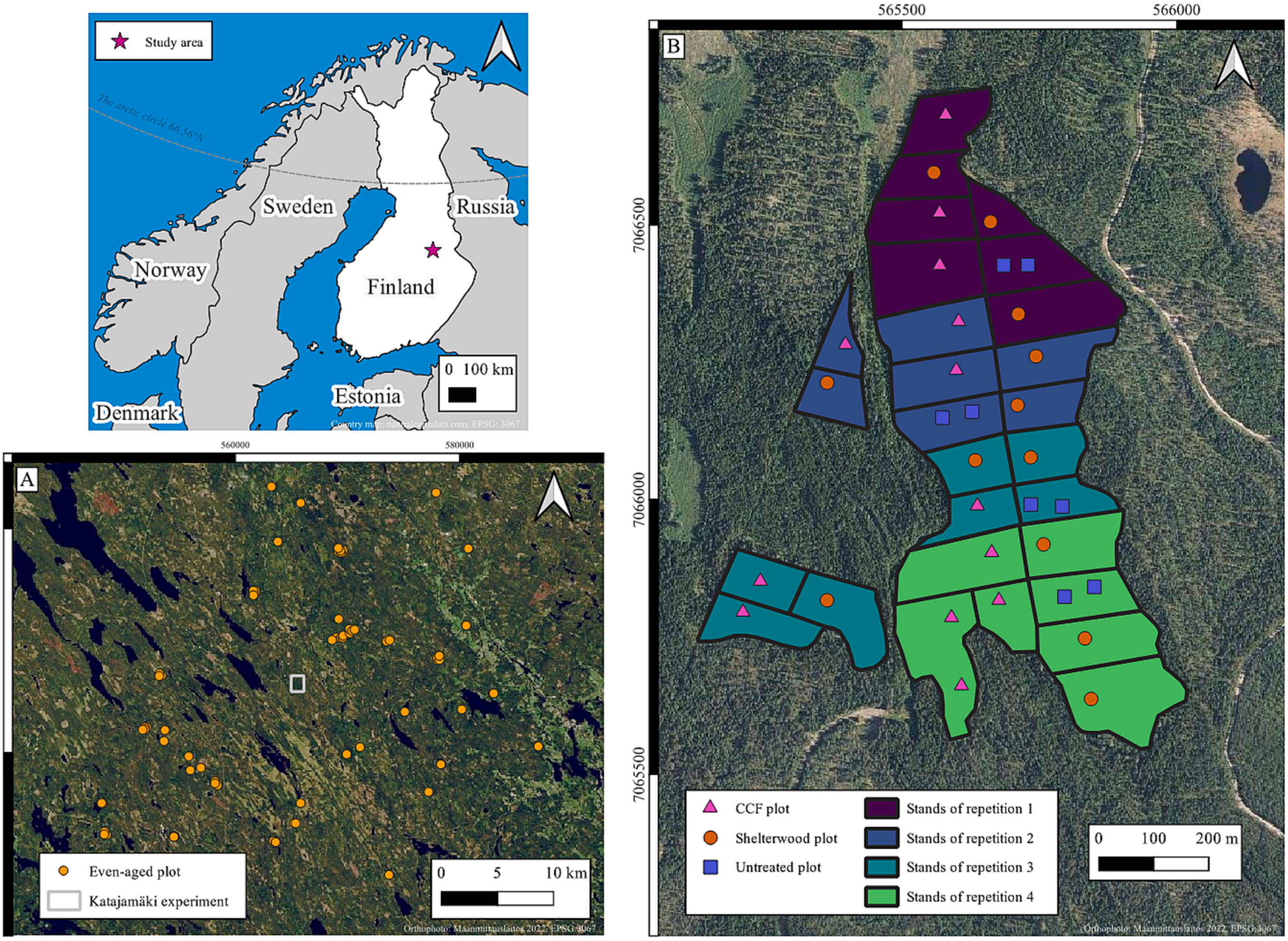

Fig. 1. Map of the Katajamäki experiment area and the even-aged plots used in the comparison of stand attribute predictions under different forest management systems. CCF denotes continuous-cover forestry.

tree height measurements (Laasasenaho 1982, Repola 2008, 2009). The tree size distribution was characterized by employing the Weibull function, where the model parameters are estimated through a maximum likelihood approach based on the measured DBH. This analysis utilized a two-parameter form of the Weibull function, encompassing the scale (b) and shape (c) parameters. The stand attributes derived from the field-measured characteristics are reported in Table 1.

As the Katajamäki experiment did not include even-aged stands, additional sample plot data from an operational forest management inventory conducted in a nearby 60 × 50 km area (center point N 63°46′ E 28°13′) were added to the data set (Fig. 1). These even-aged plots were measured by the Finnish Forest Centre in summer 2019. A total of 90 plots, evenly distributed, were selected from the following development classes: (*i*) a young thinning stand, (*ii*) an advanced thinning stand, and (*iii*) a mature stand. The field data were collected from circular plots with a radius of either 9.00 or 12.62 m, depending on the developmental stage of the forest. We chose 90 plots to provide areal coverage that corresponded to the Katajamäki experiment data. The height of one sample tree per tree species was recorded at each plot and a calibrated height model (Eerikäinen, 2009) was used thereafter to predict the height of the remaining tallied trees. Trees in the understory and dead trees were not measured in even-aged plots, but otherwise the measurements were similar to those collected for the Katajamäki experiment plots. Since the plot size was considerably smaller, however, the diameter distribution models were not fitted to the even-aged data. The tree species' proportions (of the total volume) in the even-aged data were Scots pine 38.5%, Norway spruce 38.4%, and birch 23.1%. The stand attributes of this dataset are shown in Table 1. The even-aged plot data and the ALS data are openly available at https://www.metsaan.fi/karttapalvelut (in Finnish) and at https://tiedostopalvelu.maanmittauslaitos.fi/tp/kartta, respectively.

2.2. ALS data

The ALS data were collected between 7 June and 9 July 2019 by means of a Leica ALS 80HP scanner at an altitude of 1700 m above ground level, which resulted in a nominal pulse density of 5 points per m^2 and a footprint diameter of 40 cm. The same data covered both field data sets. The ALS echoes were classified into ground and vegetation hits through the approach presented by Axelsson (2000). The ground echoes were used to create a digital terrain model (DTM). The orthometric heights of the ALS echoes were converted to above-ground heights by subtracting the DTM from the echo heights. The processing of ALS data was carried out by means of the LAStools software (rapidlasso GmbH), and ABA metrics were computed for each plot without a height threshold by using three categories of echoes: *first* of many + only echoes (f), *intermediate* echoes (m), and *last*-of-many + only echoes (l). The metrics included average (avg) and maximum (max) heights, standard deviations (std) of the heights, averages of squared heights (qav), height percentiles p5, p10, p20, …, p90, p95, and p99, canopy density percentiles b5, b10, b20, …, b90, and b95, canopy cover indices calculated from *first* echoes (cov) and all echoes (dns), and vertical complexity

Table 1
The stand attributes considered in the comparison of management alternatives. For each management approach compared, the mean value and the standard deviation value (in brackets) of each stand attribute is shown.

Attribute	Unit	CCF	Shelterwood	Untreated	Even-aged
Volume, Vol	$m^3 \cdot ha^{-1}$	187.7 (51.8)	102.9 (27.6)	231.4 (51.8)	179.4 (90.6)
Standing dead wood volume, Vol_d	$m^3 \cdot ha^{-1}$	4.1 (2.6)	1.0 (1.7)	21.9 (16.4)	
Above-ground biomass, AGB	$Mg \cdot ha^{-1}$	107.3 (24.4)	55.1 (13.9)	125.3 (23.6)	97.9 (44.5)
Basal area, G	$m^2 \cdot ha^{-1}$	25.0 (4.8)	14.6 (4.3)	28.7 (4.7)	22.3 (7.1)
Number of stems, N	N ha^{-1}	870.6 (267.0)	870.0 (622.7)	822.3 (222.8)	1251.7 (581.5)
Mean diameter, $Mean_{DBH}$	cm	17.5 (2.1)	12.1 (1.3)	19.1 (2.6)	19.3 (6.2)
Lorey's height, H_{Lorey}	m	17.5 (2.6)	17.7 (4.4)	19.1 (2.8)	16.0 (4.4)
Dominant height, H_{Dom}	m	19.8 (2.4)	17.7 (1.5)	22.0 (1.7)	18.8 (4.5)
Understory number of stems	N ha^{-1}	489.0 (299.3)	1043.0 (516.2)	198.7 (424.8)	
Understory height	m	1.9 (1.0)	2.3 (0.5)	0.5 (0.9)	
Weibull b		19.8 (2.4)	13.5 (1.4)	21.7 (2.9)	
Weibull c		2.3 (0.4)	1.5 (0.3)	2.1 (0.2)	
Number of plots		13	12	8	90

indices (see van Ewijk et al. 2011) vc1, …,vc4 with 1, 2, 3, and 4 m bin sizes, respectively. Finally, the average (int_avg) and standard deviation (int_std) values associated with the intensities were calculated, and a data transformation of the natural logarithm (ln) type was performed on each ALS metric. This was applied to all modelling steps.

2.3. Methods

To guide the modelling of stand attributes and the choice of ALS metrics, the relationship between the ALS metrics and the forest structure was **first** analyzed by comparing the ALS echo distributions with the tree height distributions across different treatments and echo categories. This included a comparison of the echo category proportions between the different treatments. In this analysis, even-aged plot data were classified by development classes.

Second, to identify the ALS variable with the most robust statistical correlation to the stand volume**,** regression models were separately fitted with the data from each treatment. The variables to be examined were selected out of a list of all model candidates. The models were validated with the relative root mean square error (RMSE) (equation 1). In the Katajamäki data set, models were constructed separately for the CCF, shelterwood, and untreated stand categories. Even-aged stands were not classified by stand development stages, which is also the current practice in Finnish forestry (Maltamo et al. 2021). The Katajamäki experimental plots were also used jointly, but the even-aged stands were not combined with the Katajamäki data set at this stage due to the different plot sizes. An ALS metric that was selected for the best independent variable for a certain category was also tested in the other categories. For the even-aged stands, RMSE% values were reported for groups of three plots, which corresponded to the approximate plot size in the Katajamäki experiment. These groups were formed according to ascending volume values in the development classes. The same procedure was followed in steps three and four, below.

In the **third** step, regression models with three independent ALS variables were constructed for volume, basal area, number of stems, mean diameter, Lorey's height, dominant height, standing dead wood volume, parameters b and c of the Weibull distribution, understory height, and number of understory stems, by using the data from the Katajamäki experiment. The variables to be examined were selected out of a list of all model candidates with 3 predictors by searching the lowest RMSE value. Models were constructed for the whole Katajamäki data set due to the small size of the different strata. Consequently, treatments were represented by treatment-specific dummy variables as such, and interactions with all predictor variables (ALS variable* treatment dummy) were also considered. Accuracy was also analyzed by treatment. In even-aged plots, corresponding models were constructed for volume, mean diameter, and dominant height.

Finally, in the **fourth** step, joint regression models were constructed for volume, mean diameter, and dominant height by using both data sets. To ensure equal weighting in the two data sets, the regression models were fitted with weighted least squares by using 33/90 as the weighting in even-aged plots. Again, treatments were represented by treatment-specific dummy variables as such, and interactions with all predictor variables (ALS variable* treatment dummy) were also considered. Accuracy was also analyzed by treatment.

In all models, we applied a t-test for the significance of all predictor variables in the models. All predictor variables were required to be significant at the level $p = 0.05$. In all cases, the accuracy of the constructed models was evaluated in terms of the root mean square error (RMSE):

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}}$$

where n is the number of plots, y_i is the observed attribute for plot i, and $\hat{y}_i$ is the predicted attribute for plot i.

In the third and the fourth step models, the mean deviation (md) was also calculated for different treatment strata as follows:

$$meandeviation = \sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)}{n}$$

Subsequently, RMSE% and md% were calculated by dividing the RMSE or md by the observed attribute mean and then multiplying the result by 100.

Since our aim was to compare management systems, not the general level of accuracy, the results were not cross-validated.

3. Results

3.1. ALS echo and tree height distributions

The tree height distributions showed bimodal forms in the CCF and shelterwood stands (Figs. 2–4). However, the proportion of tall trees in the shelterwood stand was rather small. This was also evident in the stand characteristics of this treatment (Table 1). For untreated stands, the height distribution was wide and showed considerable heterogeneity. For even-aged stands, the height distribution was unimodal for young thinning and advanced thinning stands (with slight bimodality evident in the latter), but showed clear bimodality in mature stands, which indicates that understory regeneration was present.

The ALS height distributions were unimodal for the *first*, *last,* and *intermediate* echoes for the CCF and untreated stands (Figs. 2–4). In all cases, these distributions also included peaks for ground echoes. For the shelterwood stands, the distributions showed a descending trend. Thus the correspondence between tree height distributions and ALS height distributions varied across management experiments. The closest correspondence was found in the untreated stands, whereas the bimodal form of the CCF height distribution was not evident in the ALS heights. In the shelterwood stands, the correspondence was the closest for

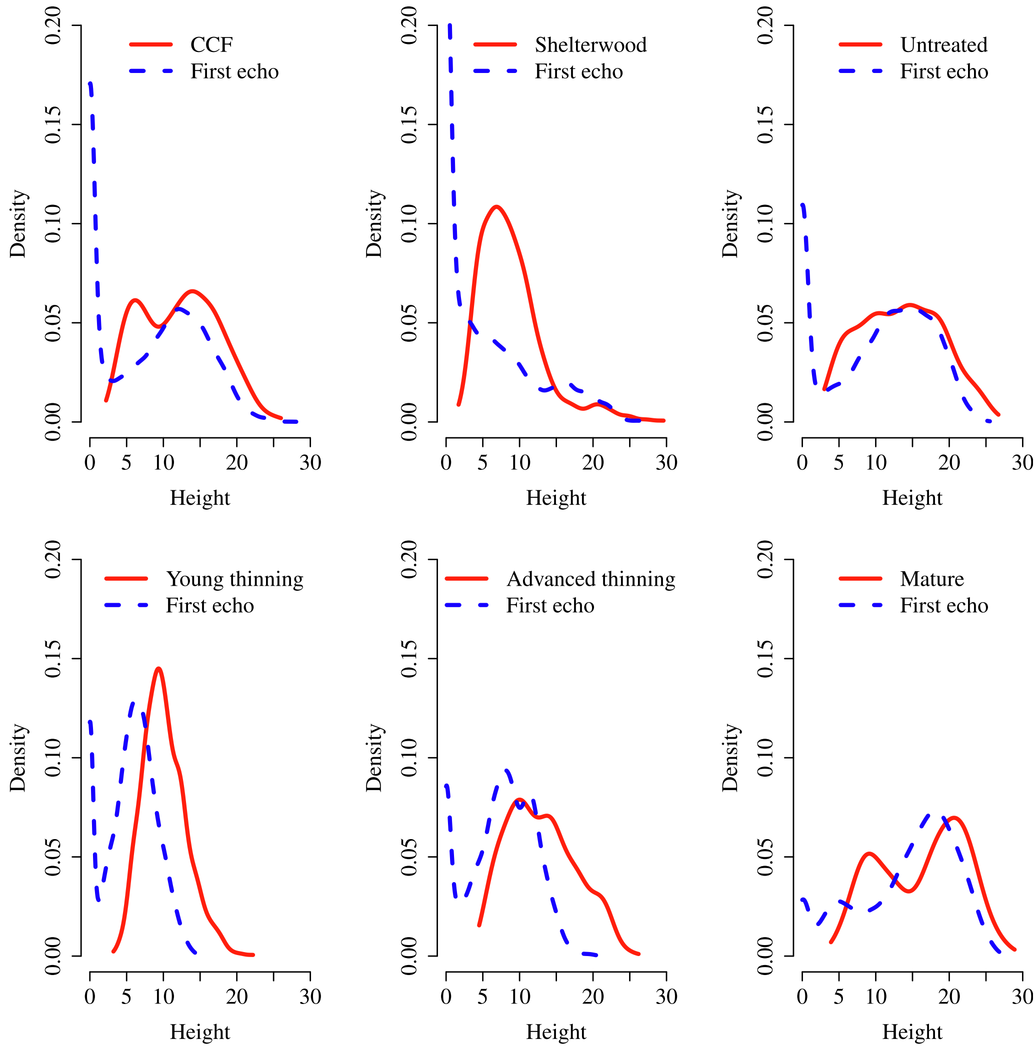

Fig. 2. Relationship between airborne laser scanning (ALS) *first* echo distributions (blue dashed line) and tree height distributions (red solid line) across the different treatments. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

intermediate echoes.

In even-aged stands, the shape of the *first* and the *last* echo height distributions followed the tree heights most closely (Figs. 2–4). This was the case in the unimodal young thinning stands, the advanced thinning stands (with very slight bimodality), and the bimodal mature stands characterized by the *first* echo ALS data. Exceptionally, though, the *last* echo data did not describe the bimodality of the tree heights in the mature stands. Another close correspondence was seen in the *intermediate* category, though there was more variation in the ALS height distributions.

As regards the proportions of the ALS height categories (Table 2), the proportions of the *first* and the *last* echoes were usually close to each other. The largest proportion of *intermediate* echoes occurred in the mature stands and the smallest in the young and shelterwood stands.

To conclude, both the tree height and the ALS height distribution and their mutual correspondence differed across the forests. This led us to look for an ALS-based independent variable that would perform best in terms of modelling the stand volume under the different management categories.

3.2. Single-independent-variable models for predicting the stand volume

In this step we constructed optimal regression models with one independent ALS variable for volume in both the Katajamäki data set and the even-aged data set (Table 3). The results showed that the best independent variable in the Katajamäki data set was the average height of the *first* echo (or its transformation) in three cases out of four. This variable also performed fairly well in even-aged stands. In untreated stands, a density metric of *intermediate* echoes was found to be the best performing independent variable, though it performed poorly in the other categories. The same was true for the best metrics in even-aged stands, i.e., the standard deviations associated with *intermediate* echoes. Overall, the accuracy of the stand volume predictions varied considerably across the different categories. In the CCF plots, the RMSE % value was the lowest.

3.3. Three-independent-variable models for the essential stand variables

The decision to construct models with three independent variables was based on the observation in step two that certain ALS metrics appeared to be most effective for specific management systems. The models were constructed for a set of essential stand attributes (Table 4). The results of the single-independent-variable models were not utilized as such, so that the selected metrics changed (Appendix).

In general, the R^2 values of the models were fairly high (Appendix). Due to the nonlinear relationship, there was a need to transform the dependent variable for the number of stems in the Katajamäki data set and the volume in the even-aged data set. One notable result was the

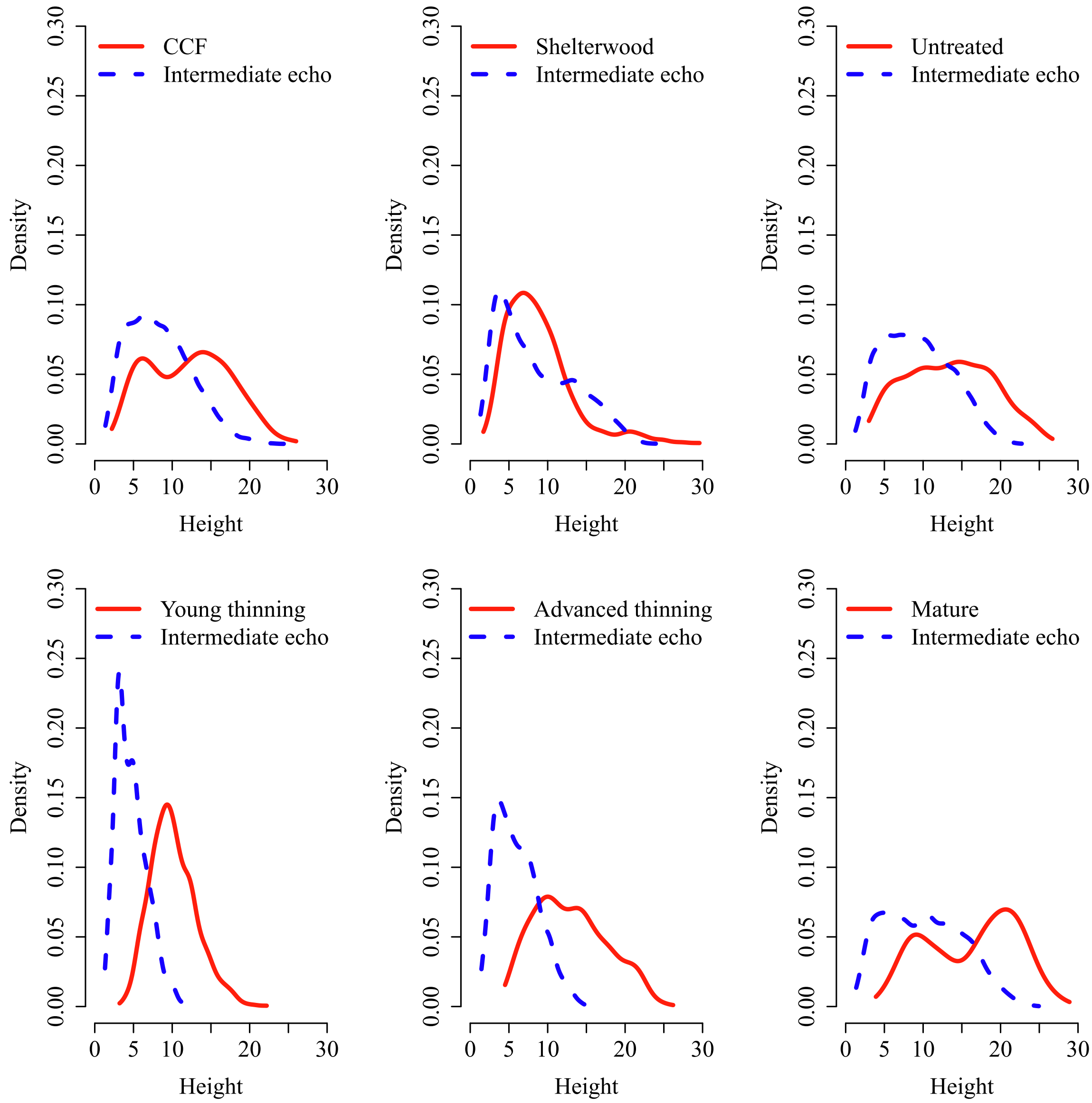

Fig. 3. Relationship between airborne laser scanning (ALS) *intermediate* echo distributions (blue dashed line) and tree height distributions (red solid line) across the different treatments. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

large proportion of metrics based on *intermediate* echoes. In the case of the volume model, two out of three independent variables were the densities of *intermediate* echoes, and all variables were *intermediate* echo type metrics for the mean height. The role of intensity-based independent variables came out emphatically in the case of the model for understory height. It is also worth noting that the selected independent variables were the same for the Weibull parameter *b* and the mean diameter, which is logical, for those attributes are very closely related to each other. Although the variation between the different treatments was high, the dummy variables that were indicative of these differences were significant in the models for dominant height and the number of stems only. However, some of the other dummy variables were close to being significant. Thus, it seemed that a combination of three independent variables was capable of accurately describing the differences irrespective of the management types. This was also emphasized by the fact that various metrics, such as the squared average of *last* echoes (l_qav), had a more linear relationship with the stand attributes than the basic ALS height metrics did (Fig. 5).

The accuracies of the models constructed are presented for both the modelling data sets and those for the different strata in Table 4. In this assessment, the three even-aged plots were again combined. Both the RMSE and the mean deviation values were rather low for most of the attributes. In the comparison of the management types, untreated stands exhibited the lowest values for most of the attributes. An exception was the number of stems, where the shelterwood stands had a very low value (6.94%). As expected, the most difficult attributes to characterize were the standing dead wood volume and the understory attributes, where the accuracy varied considerably between the categories. For these attributes, the mean deviations were also the largest. While the amount of deadwood was predicted rather accurately for the untreated stands, this was not the case for the shelterwood stands. Then again, the understory was predicted well for the shelterwood stands. For CCF, the accuracy was moderate in regard to all three attributes. In comparison with the even-aged stands, the accuracy associated with the CCF stands was greater for the volume predictions but lower for the mean diameter prediction. In general, the differences between the CCF and the even-aged plots were small.

The size (DBH) distributions of the stands were characterized by applying the two-parameter form of the Weibull function. This required that the underlying population of diameters not be multimodal. A visual

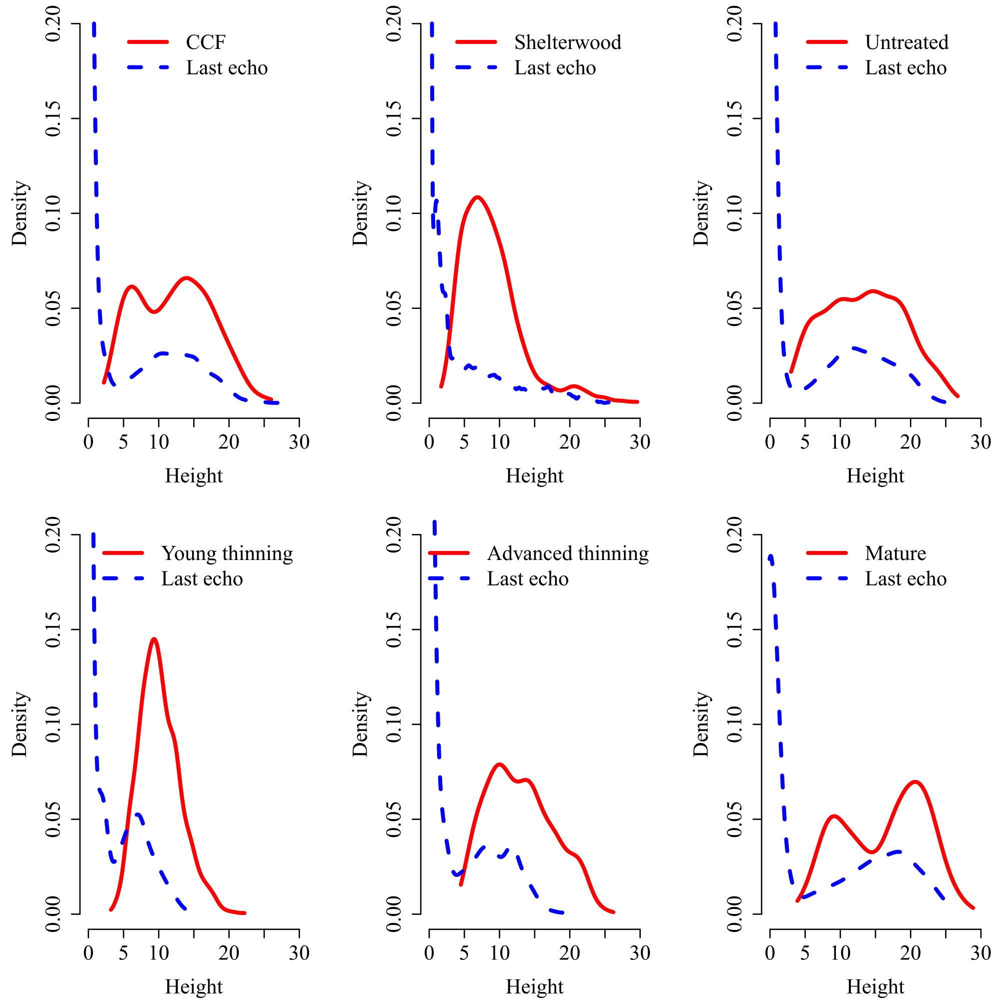

Fig. 4. Relationship between airborne laser scanning (ALS) *last* echo distributions (blue dashed lines) and tree height distributions (red solid line) across the different treatments. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Proportions of different echo categories, *first* (f), *last* (l) and *intermediate* (m), in the different treatments comprising continuous cover forestry (CCF), shelterwood stands, untreated stands, and three even-aged stands divided into young thinning, advanced thinning, and mature stand development classes.

	f	l	m
CCF	0.44	0.44	0.12
Shelterwood	0.47	0.47	0.06
Untreated	0.44	0.43	0.13
Young thinning	0.46	0.46	0.08
Advanced thinning	0.44	0.44	0.12
Mature	0.41	0.41	0.18

check showed that most of the stands had a unimodal or descending diameter distribution. An example from the CCF category, a right-skewed distribution, is presented in Fig. 6. The Weibull fits of estimated and predicted distributions were fairly close to each other, and the description of the underlying tree population by Weibull could be considered adequate.

3.4. Joint models for selected stand attributes

The final modelling step was to construct joint models for the volume, the dominant height, and the mean diameter by using the data sets from Katajamäki and from the even-aged stands simultaneously. The models constructed are presented in the Appendix, and their associated accuracies are shown in Table 5.

The model for the volume included only *first* echo metrics, whereas the previous separate models included two *intermediate* echo metrics. The volume model was also the only model where a dummy variable with regard to the CCF stands was found to be statistically significant. Correspondingly, the dominant height model was the only model where the interaction ALS metric * dummy was found to be statistically significant. This was the case for metric l_h90 in the untreated and the CCF stands. In general, the RMSE% values increased slightly in comparison with the separate models. For the volume, the RMSE% value for CCF was considerably smaller but was greater for the shelterwood and untreated stands. The changes were the most notable for the mean diameter and the smallest for the dominant height. This suggests that the combining data sets of the different management types were the most challenging in cases where the management approach strongly affected the value of the variable of interest.

4. Discussion

This study examined the prediction of a set of stand attributes under different forest management systems by applying the ABA approach to ALS data. Our experiment in Katajamäki included CCF, shelterwood, and untreated stands. The experiment had been initiated in the 1980's and, as even-aged stands were missing, we used some operational forest

Table 3
Selected airborne laser scanning (ALS) metrics for volume prediction in the different treatments according to the root mean squared error (RMSE%) values obtained. The lowest RMSE values for each treatment are shown in bold. All selected independent variables were also tested in other categories. ln denotes the natural logarithm transformation of the variable, *f* denotes the *first* echo, and *m* denotes the *intermediate* echo. For more information on the abbreviations for the ALS metrics, see section 2.2.

	Katajamäki experiment, all plots	Katajamäki experiment, CCF	Katajamäki experiment, Shelterwood	Katajamäki experiment, Untreated	Even-aged plot data
Best independent variable	f_avg	f_avg	ln_f_avg	ln_m_b50	m_std
f_avg	**11.59**	**6.91**	15.02	10.33	17.55
ln_f_avg	14.16	7.31	**14.57**	9.76	21.30
ln_m_b50	34.01	24.98	21.51	**6.88**	41.86
m_std	39.90	13.78	25.51	18.10	**17.45**

Table 4
The relative root-mean-square error (RMSE%) and the relative mean deviation [md%] (in brackets) associated with the stand attribute models constructed separately for the Katajamäki and the even-aged data sets. In the Katajamäki data set, the RMSE% is also presented for the different treatments.

	Katajamäki, all plots	Katajamäki, CCF	Katajamäki, Shelterwood	Katajamäki, Untreated	Even-aged plots
Volume	8.48	8.91 (2.6)	12.61 (4.4)	6.11 (1.2)	12.95
Above-ground biomass	8.23	8.38 (1.8)	11.65 (-0.6)	5.45 (-2.2)	
Basal area	8.56	8.38 (-0.5)	10.60 (-0.5)	7.01 (0.9)	
Number of stems	15.67	17.07 (3.3)	6.94 (1.5)	22.18 (-5.9)	
Mean diameter	8.32	7.38 (0.1)	9.31 (-1.8)	8.47 (2.5)	6.6
Lorey's height	9.39	10.46 (0.9)	9.34 (-0.5)	7.73 (-0.5)	
Dominant height	2.59	2.83 (0.1)	2.81 (-0.1)	1.89 (0.1)	2.19
Deadwood volume	47.72	52.47 (7.7)	262.37 (-35.3)	26.13 (0.0)	
Weibull b	8.16	7.45 (-0.6)	8.90 (2.3)	8.22 (2.0)	
Weibull c	9.08	8.45 (1.2)	12.24 (-2.3)	6.48 (-0.2)	
Understory height	30.96	34.14 (7.1)	15.25 (0.8)	107.7 (-34.7)	
Understory number of stems	39.76	53.38 (-1.0)	19.42 (1.6)	141.0 (-46.3)	

inventory plots located near Katajamäki for our analyses. These additional plots included only part of the measurements made on the Katajamäki plots, and thus our only comparisons between the Katajamäki stands and the even-aged stands pertained to stand volume, dominant height, and mean diameter. In the performance assessment, the differences in plot size between the even-aged and the Katajamäki plots were controlled for. It should be noted, however, that the comparison between even-aged stands and those under other management systems was based on different plot types measured for different purposes.

In general, the results indicated that stand attributes under different management systems can be successfully predicted by using joint models that are indifferent to treatment. Although the tree height and the ALS echo height distributions differed between the management systems and the one-independent-variable models showed a number of best independent variables, the three-independent-variable models accounted for these differences. Dummy variables or interactions that showed treatment-level differences were statistically significant in a few cases only. Most notably, the models often included ALS metrics that described average and squared average height. In general, this was also the case for metrics of the *intermediate* echo type. This may be partly due to sensor development over the years; the portion of *intermediate* echoes is currently larger than it was with the early-generation sensors. Due to missing values, however, these metrics may still prove problematic in operational wall-to-wall applications.

The accuracy figures associated with the models showed rather low RMSE% values. For example, the RMSE% values associated with the number of stems ranged from 7 to 22%, whereas values of over 30% had often been obtained in earlier studies (Maltamo et al. 2009, Packalén and Maltamo 2007). This is partly due to the small geographical variation of our data and the large field plots. Still, our values also showed good predictability of stand attributes in all the management systems considered in this study. The RMSE% values in our study are comparable to those obtained at the stand level by Suvanto et al. (2005) in even-aged forests, though the variation across treatments was considerable in our study (Table 1).

Surprisingly, the diameter distributions obtained in the Katajamäki experiment did not show multimodal forms. Consequently, it was possible to predict the parameters of the Weibull function with RMSE% values $< 10\%$. This result differed from those of the Bollandsås and Næsset study (2007), where bimodal diameter distributions in forests of the CCF type were characterized by percentile-based distribution models predicted by ALS metrics. Due to the small sample plot sizes, diameter distribution in even-aged stands was not considered in our study.

In the case of standing deadwood, our results were fairly accurate, particularly in untreated stands. The RMSE% value of 26% was considerably lower than the 78.8% value presented by Pesonen et al. (2008) for their study area in the Koli National Park. Corresponding figures for managed areas have also been considerably higher (Keränen et al. 2015). In general, our study further confirms the good predictability of standing deadwood by ALS metrics in forest areas with high volumes of deadwood.

In CCF and shelterwood forests, attributes of the understory are the focus of special interest. Our results were fairly good in the CCF plots and especially good in the shelterwood plots. The predictability of stand attributes in CCF differed from that found in Bollandsås et al. (2008), who concentrated on the prediction of understory regeneration. However, their research design was different from ours, so that no direct comparison can be made. Our estimates can also be compared with those presented Maltamo et al. (2005), where similar accuracies were obtained for these stand characteristics in untreated forest areas.

To date, there are few studies in which ALS data have been used in forest management experiments. Even in these few studies, the focus has been on the management of the forest, not on the inventory (Sumnall et al. 2017). One reason for this is that many experiments tend to be located in large areas analogous to the ERIKA plot network in Finland, for instance. Such large areas cannot be covered by a single ALS

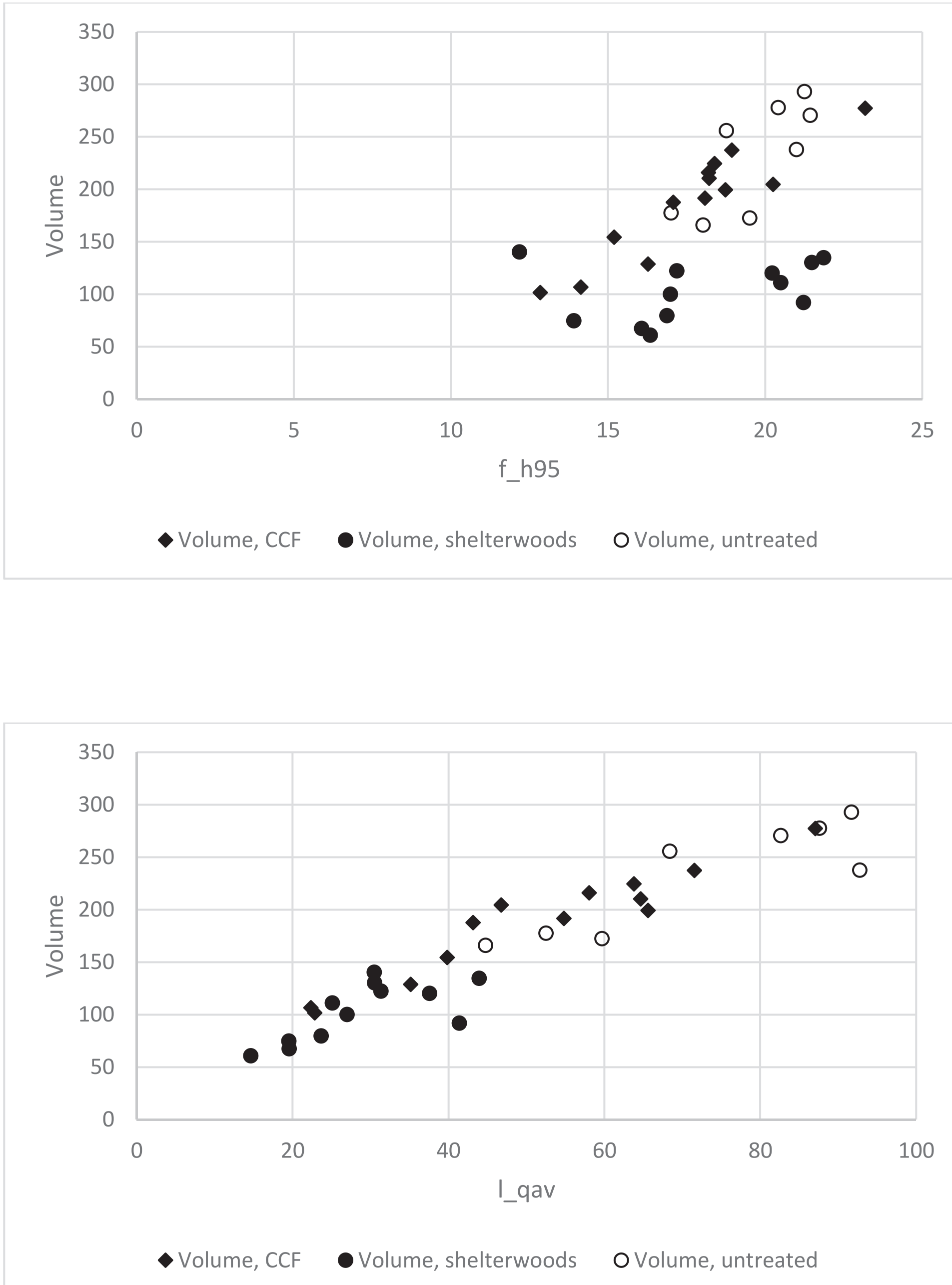

Fig. 5. Relationship between volume and an airborne laser scanning (ALS)-based 95th percentile of *first* echoes (f_h95) (above), and between volume and squared average height of *last* echoes (l_qav) (below).

campaign. In this regard, sensor effects can have a strong influence on the results. The other extreme is experiments carried out in very small areas with little variability, such as our Katajamäki experiment. A recent comparable study was presented by Cosenza et al. (2022), who reported on a silvicultural experiment that applied laser scanning data collected by means of an uncrewed aerial vehicle (UAV). The data, collected to test fertilization and weed control, included 24 plots, each 252 m^2, in Florida, United States. In their study they successfully tested plant area metrics based on UAV laser scanning data with a very high point density (275 points per m^2) against traditional ABA metrics. Although UAV data was an option for our study as well, we regarded such data as an unrealistic option, for our aim was to discuss results obtained for larger areas.

The promising results presented in this study were related to joint modelling of stand attributes for different forest management types. We conclude that for changing the forest management practices, ALS-based forest inventory models may be used without stratifying the area into different management types. Despite our largely promising results, more research is required to overcome the limitations posed by the size of our study area and the tree species considered. Further studies should also give closer consideration to the number, size, and species distribution of the small-sized understory trees that grow under the dominant tree canopy. And besides the area-based approach, single-tree detection of ALS data should also be examined.

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CRediT authorship contribution statement

M. Maltamo: Conceptualization, Data curation, Formal analysis,

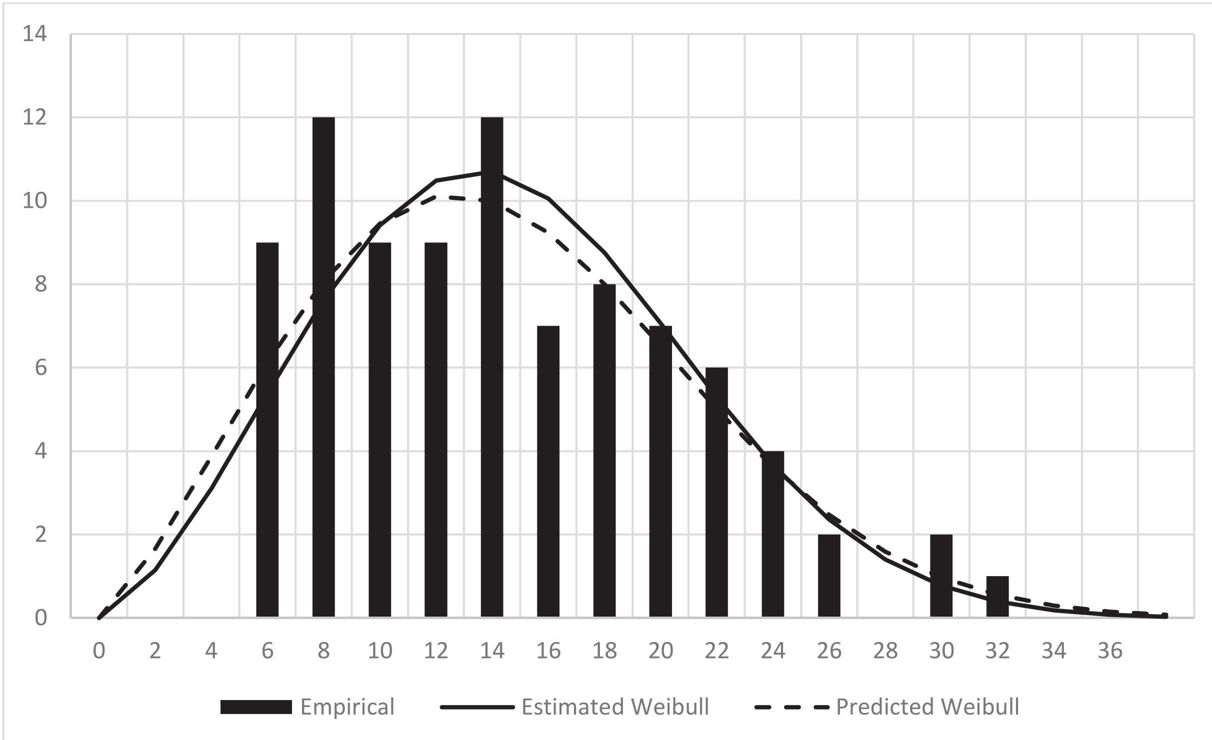

Fig. 6. An example of the predicted Weibull distribution in a stand managed by continuous-cover forestry (CCF). The Weibull parameters estimated by using observed tree diameter at breast height (DBH) are b = 2.5 and c = 16.5. The corresponding predictions are b = 2.29 and c = 16.31.

Table 5
The root mean squared error (RMSE%) and the relative mean deviation [md%] (in brackets) values associated with the stand attribute models constructed by applying the joint models for the Katajamäki and the even-aged datasets. In the Katajamäki data set, RMSE% is also presented for the different treatments. CCF denotes continuous cover forestry.

	Katajamäki	CCF	Shelterwood	Untreated	Even-aged
Volume	11.23 (0.4)	6.91 (0.8)	19.42 (0.1)	10.48 (-1.0)	13.15 (0.4)
Dominant height	4.00 (0.0)	2.78 (0.0)	5.56 (-0.2)	3.07 (-0.2)	2.79 (0.0)
Mean Diameter	13.95 (0.1)	14.8 (2.6)	17.69(-2.1)	8.41(-0.6)	8.08 (-0.1)

Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization. **P. Peltola:** Data curation, Formal analysis, Investigation. **P. Packalen:** Conceptualization, Methodology, Software, Validation, Visualization. **A. Hardenbol:** Data curation. **J. Räty:** Data curation, Methodology, Visualization. **T. Saksa:** Conceptualization, Data curation, Resources. **K. Eerikäinen:** Conceptualization, Methodology. **L. Korhonen:** Software, Supervision, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Part of field data is available on request, part is open data from Finnish Forestry Center. Remote sensing data is open data by National Land Survey of Finland.

Appendix

The models constructed for the stand attributes in the different data sets. The attributes considered are described in Table 1 and the area-based approach (ABA) metrics applied are shown in Section 2.2. The t-values of the predictor variables are given in parentheses after each coefficient. In addition to the models, the residual variance and r-square (R^2) values are presented. ε_i denotes residual error in plot i. Dummy variables include the continuous-cover forestry (CCF) and untreated treatments.

Katajamäki experiment data

$$Volume = \text{-1361.66 (-5.2)} + \text{2.42 (18.5) l\_qav} + \text{415.84 (5.6) ln\_m\_b70} - \text{6.02 (-5.9) m\_b60} + \varepsilon_i$$

$\mathrm{var}(\varepsilon_i) = 15.15\hat{}2$, $R^2 = 0.95$

$$AGB = \text{284.77 (5.9)} + \text{79.39 (6.1) ln\_f\_b20} - \text{138.78 (-6.6) ln\_f\_b40} + \text{46.41 (5.7) ln\_l\_avg} + \varepsilon_i$$

$\mathrm{var}(\varepsilon_i) = 8.14\hat{}2$, $R^2 = 0.95$

$$Vol_d = \text{44.43 (3.2)} - \text{13.27 (-7.4) f\_h10} + \text{6.48 (10.5) f\_h20} - \text{49.01 (-3.1) m\_vc2} + \text{4.62 (2.2) untreated} + \varepsilon_i$$

$var(\varepsilon_i) = 3.78\hat{}2.14$, $R^2 = 0.91$

$$sqrt(N) = 38.18\ (4.9) - 4.65\ (-6.0)\ l\_avg + 0.85\ (4.8)\ l\_dns - 5.93\ (-4.3)\ ln\_f\_b05 + \varepsilon_i$$

$var(\varepsilon_i) = 2.46\hat{}2$, $R^2 = 0.84$

$$G = 28.15\ (3.9) + 1.06\ (7.0)\ f\_h60 + 0.26\ (3.1)\ l\_dns - 6.93\ (-3.6)\ ln\_m\_b40 + \varepsilon_i$$

$var(\varepsilon_i) = 2.02\hat{}2$, $R^2 = 0.93$

$$H_{Dom} = 5.35\ (6.2) - 1.13\ (-2.8)\ f\_max + 1.50\ (3.7)\ l\_max + 0.48\ (15.0)\ l\_h90 + 0.58\ (2.1)\ untreated + \varepsilon_i$$

$var(\varepsilon_i) = 0.55\hat{}2$, $R^2 = 0.96$

$$H_{Lorey} = -237.26\ (-4.9) + 49.76\ (4.8)\ ln\_m\_b80 - 13.61\ (-3.1)\ ln\_m\_h05 + 24.48\ (7.6)\ ln\_m\_h50 + \varepsilon_i$$

$var(\varepsilon_i) = 1.8\hat{}2$, $R^2 = 0.74$

$$mean_{DBH} = 39.66\ (5.8) + 1.28\ (12.6)\ l\_h90 - 30.06\ (-6.2)\ l\_vc0 - 8.04\ (-3.8)\ ln\_m\_max + \varepsilon_i$$

$var(\varepsilon_i) = 1.41\hat{}2$, $R^2 = 0.86$

$$\text{Weibull c} = -49.63\ (-6.1) - 0.056\ (-11.3)\ f\_b70 - 0.11\ (-6.9)\ f\_h80 + 6.17\ (6.9)\ ln\_f\_int\ std + \varepsilon_i$$

$var(\varepsilon_i) = 0.19\hat{}2$, $R^2 = 0.83$

$$Weibullb = 45.48\ (6.0) + 1.48\ (13.0)\ l\_h90 - 33.71\ (-6.3)\ l\_vc0 - 9.48\ (-4.0)\ ln\_m\_max + \varepsilon_i$$

$var(\varepsilon_i) = 1.56\hat{}2$, $R^2 = 0.87$

$$Understoryheight = 193.93\ (4.9) - 0.47\ (-7.7)\ f\_h30 - 13.63\ (-5.0)\ ln\_l\_int\ avg - 5.85\ (-3.3)\ ln\_l\_int\ std + \varepsilon_i$$

$var(\varepsilon_i) = 0.57\hat{}2$, $R^2 = 0.74$

$$\text{Understory N} = 633.54\ (2.7) + 45.36\ (6.9)\ f\_b10 + 802.34\ (9.2)\ f\_h10 + 2531.28\ (4.2)\ ln\_l\_vc0 + \varepsilon_i$$

$var(\varepsilon_i) = 263.12\hat{}2$, $R^2 = 0.78$.

Even-aged stands

$$sqrt(Vol) = -12.06\ (-9.3) + 2.74\ (10.1)\ ln\_qav + 0.0013\ (6.0)\ m\_int\ std + 0.21\ (5.8)\ m\_h60 + \varepsilon_i$$

$var(\varepsilon_i) = 1.1\hat{}2$, $R^2 = 0.90$

$$H_{Dom} = -21.89\ (-4.7) + 7.08\ (5.7)\ ln\_l\_b80 + 1.02\ (46.9)\ f\_h90 - 6.59\ (-3.6)\ vc1 + \varepsilon_i$$

$var(\varepsilon_i) = 0.79\hat{}2$, $R^2 = 0.97$

$$mean_{DBH} = -26.55\ (-8.8) + 5.78\ (9.1)\ ln\_l\_b70 + 1.25\ (20.9)\ f\_max + 2.38\ (3.7)\ l\_b10 + \varepsilon_i$$

$var(\varepsilon_i) = 2.01\hat{}2$, $R^2 = 0.90$.

Joint models.

$$sqrt\ (.Vol) = -51.44\ (-5.7) + 1.20\ (25.3)\ f\_avg + 12.21\ (6.2)\ ln\_f\_b90 - 0.25\ (-7.3)\ f\_h20 + 0.51\ (2.1)\ ccf + \varepsilon_i$$

$var(\varepsilon_i) = 0.72\hat{}2$, $R^2 = 0.89$

$$\begin{aligned} H_{Dom} = -59.78\ (-4.4) + 14.37\ (4.8)\ ln\_l\_b90\ + 0.74\ (13.5)\ l\_h90 \\ +0.36\ (9.3)\ m\_h95 \pm 0.05\ (-2.1)\ untreated{*}l\_h90 \\ -0.055\ (-2.4)\ ccf{*}l\_h90 + \varepsilon_i \end{aligned}$$

$var(\varepsilon_i) = 0.65\hat{}2$, $R^2 = 0.94$

$$mean_{DBH} = -26.6\ (-7.5) + 0.17\ (6.2)\ f\_b80 + 0.0023\ (12.4)\ m\_int\ std + 1.17\ (17.2)\ l\_h90 + \varepsilon_i$$

$var(\varepsilon_i) = 1.74\hat{}2$, $R^2 = 0.80$.

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