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THE TRANSFERABILITY OF AIRBORNE LASER SCANNING BASED TREE LEVEL MODELS BETWEEN DIFFERENT INVENTORY AREAS

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1 **THE TRANSFERABILITY OF AIRBORNE LASER SCANNING BASED TREE LEVEL**
2 **MODELS BETWEEN DIFFERENT INVENTORY AREAS**

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ABSTRACT

In this paper we examine the transferability of airborne laser scanning (ALS) based models for individual tree detection (ITD) from one ALS inventory area (A1) to two other areas (A2 and A3). All areas were located in eastern Finland < 100 km from each other and were scanned using different ALS devices and parameters. The tree attributes of interest were diameter at breast height (Dbh), height (H), crown base height (Cbh), stem volume (V) and theoretical sawlog volume (Vlog) of Scots pines with Dbh $\geq$ 16 cm. All trees were first segmented from the canopy height models, and various ALS metrics were derived for each segment. Then only the segments covering correctly detected pines were chosen for further inspection. The tree attributes were predicted using the k-nearest neighbor (k-nn) imputation. The results showed that the relative root mean square errors increased for each attribute after the transfers: Dbh 13.5% (A1) to 14.8% (A2) / 18.1% (A3), H 3.2% to 5.9% / 6.2%, Cbh 13.3% to 15.3% / 18.3%, V 29.3% to 35.4% / 39.1% and Vlog 38.2% to 54.4% / 51.8%. The observed values indicate that it may be possible to employ ALS based tree level k-nn models over different inventory areas without excessive reduction in accuracy, assuming that the tree species is known to be similar.

Keywords: airborne laser scanning, individual tree detection, k-nearest neighbor, k-nn, transferability

42 INTRODUCTION

43 Airborne laser scanning (ALS) has proved to be very useful in forest inventories (e.g. Vauhkonen
44 et al. 2014a). The two main approaches for deriving forest information from ALS data are the
45 area based approach (ABA) and individual tree detection (ITD). Compared to ITD, several
46 studies have shown ABA provides more accurate plot and stand level statistics of forest
47 attributes, such as total volume (Peuhkurinen et al. 2011), basal area (Lindberg & Hollaus 2012),
48 aboveground biomass (Kankare et al. 2013) and aboveground carbon density (Coomes et al.
49 2017).

50 The main reasons why ABA usually performs better than ITD are the difficulty in predicting stem
51 diameter from the tree height observed in ITD and the fact that only the dominant trees are
52 usually detected (Vauhkonen 2010a). Errors in species classification introduce additional
53 uncertainty into the ITD-based tree attributes, because the tree height-diameter relationships are
54 species-specific. However, ITD methods are promising for pre-harvest inventories of marked
55 stands where the tree species is often known in advance, and understory trees have been removed
56 in thinnings (Vastaranta et al. 2014; Vauhkonen et al. 2014b). Under such conditions, ITD could
57 potentially provide better timber quality information than ABA, because stem quality attributes
58 such as branch height properties can potentially be derived separately for each tree (Maltamo et
59 al. 2009b, Vauhkonen et al. 2014b).

60 Both ABA and ITD require laborious and expensive field data for the calibration of the statistical
61 models used in estimation and mapping. There are several ways to decrease the costs of field
62 work, such as the use of field data from national forest inventories (Maltamo et al. 2009a) or the
63 utilization of existing models or data from earlier ALS inventories, i.e. applying an old model to a
64 new area and data set. Models that perform well in such scenarios have good transferability.

65 Practical inventories, however, are most often performed using different ALS devices and
66 scanning parameters, and the structure of forests or individual trees can vary notably between
67 areas as well. These aspects make the utilization of earlier models less accurate and prone to bias,
68 although in some situations the loss of accuracy may be small enough to be acceptable (Kotivuori
69 et al. 2016).

70 Different ALS devices, even if they would represent the same model, may produce remarkably
71 different point clouds (Næsset 2009, Korpela et al. 2010). On the other hand, it is possible that
72 the estimates based on point clouds produced by a certain device can be notably more accurate in
73 one place than in another (Kotivuori 2016). In addition to device type, the scanning parameters
74 that are used can have degenerative effects on the results. Yu et al. (2004) reported that the mean
75 error of associated with height estimations increased from 0.77 m to 1.16 m when the flying
76 altitude was elevated from 400 m to 1500 m. However, several studies have shown that changes
77 in flight altitude do not necessarily cause considerable differences between the predictions made
78 locally with linear models (e.g. Næsset 2004, Görgens et al. 2015).

79 In addition to the effects of ALS devices and scanning parameters, forest structure can also cause
80 problems in transferability, particularly if the source and target locations differ from each other,
81 for example, by tree species proportions or systematically by the shapes of individual tree
82 crowns, or if the reference data does not cover all the variation exhibited in the validation data. In
83 Finland, variations in topography and climate result in considerably larger mean volumes in the
84 south of the country than in the north (Korhonen et al. 2017).

85 The strength of the returning echo (i.e. intensity value) along with 3D coordinates can be
86 analyzed. However, sensor manufacturers measure and define the intensity value in different
87 ways (Wagner et al. 2004), and scan and acquisition parameters, such as flight altitude and
88 weather conditions also influence the intensity (Holopainen et al. 2013). Therefore, ALS metrics

based on intensity values can differ considerably between different areas. By normalizing the intensity values, it is possible to decrease the effects of varying target-to-sensor distances (e.g. caused by scanning angle and presence/absence of hills) and to improve the fusion of two or more ALS datasets from the same area (Korpela et al. 2010). Korpela et al. (2010) also noticed that intensity metrics could potentially be used to recognize some broadleaved deciduous tree species directly from the ALS data.

The transferability of ALS based models has been studied previously, but so far, the focus has been on stand level ABA applications. Nilsson et al. (2016) studied the accuracy of linear regression models created from 11,500 Swedish NFI field sample plots and ALS data from 13 different devices for the prediction of stem volume and basal area. At the plot level, the relative root mean square error (RMSE) values associated with volume and basal area varied between 19.2-25.1% and 20.4-26.7%, respectively. Kotivuori (2016) studied the transferability and calibration of ABA models at the national scale in Finland. General models for dominant height, volume and biomass were created using nine different ALS datasets from various locations in Finland. These general models were slightly less accurate than the local models, but they could be improved by calibrations. Uuttera et al. (2006) researched the transferability of plot level mixed effect models created with the Generalized Least Squares method. The modeling and two validation areas were located in central- and southeastern Finland within a few hundred kilometers from each other, and the ALS data acquisitions were performed with the same device and practically the same parameters. Nevertheless, the accuracy decreased notably; the relative RMSE value of plot volume increased from 9.8% to 17.8-18.8%, although some of the resulting RMSE values were still reasonable. In addition, regression models originally created in Norway were evaluated, and resulted in relatively satisfactory RMSE values of 24-28%. In Gopalakrishnan et al. (2015), a wall-to-wall canopy height map was generated over a sample area

of 9.2 x 9.2 km in southeastern USA. For each 120 x 120 m cell, dominant height was predicted with a regression model that yielded a RMSE value of 3.0 m. The model was based on data from 76 separate ALS inventories and 1,800 field sample plots. The study showed the feasibility of their methodology to generate coherent wall-to-wall canopy height maps over large areas.

Maltamo et al. (2012) examined the calibration of tree-level ALS models for diameter at breast height (Dbh), height (H), crown base height (Cbh), height of the lowest dead branch, and total stem volume (V) within a single inventory area. They divided 70 plots into separate training and validation datasets (56 + 14 plots, respectively). The models created with a seemingly unrelated mixed-effects (SUR) technique were calibrated with the best linear unbiased predictor (BLUP) method, and in some cases the RMSE values and mean prediction errors were successfully decreased. For example, by calibrating the model that predicted the height of the lowest dead branch with field measurements from 10 sample trees, the RMSE value decreased from 2.1 m to < 1.4 m, which was a considerable improvement.

In this study, we fit a k-nearest neighbor (k-nn) model for the simultaneous prediction of multiple individual tree attributes in one area (training area), and apply the model to predict the attributes for two other areas (validation areas). All areas were scanned using different sensors and parameters. We restricted the study to managed, commercially valuable stands with sawlog-sized Scots pines (*Pinus sylvestris*), where it is realistic to assume that dominant trees are detected and that their species is already known. Tree-level quality attributes would be valuable in such forests if they could be obtained directly from ALS data using existing models. The attributes of interest were Dbh, H, Cbh, V and the theoretical volume of the sawlog-sized stem (Vlog) of the sawlog-sized pines. "Transferability" was assessed based on the observed RMSE% and BIAS% values of the tree level attributes in the different areas.

137

138 **MATERIAL AND METHODS**

139 The data used in this study consisted of three different inventory areas in eastern Finland. The
140 data from the Liperi inventory area (hereafter A1) was used as training data, whereas datasets
141 from Kiihtelysvaara (A2) and Koli (A3) inventories were used for validation. The shortest
142 Euclidian distance between plots in A1 and A2 was approximately 50 km, and the distance
143 between plots in A1 and A3 was 62 km (Figure 1). All areas contain a mixture of forests with
144 different soils, dominant species, age classes and management histories. The average size of a
145 stand is about two hectares in all areas, and maximum tree height in old growth forests is about
146 30 m depending on the site.

147 In A1 and A2, the forests are privately owned and managed more or less intensively depending
148 on the owner. In A3, the field plots were located in the conservation area of the Koli National
149 Park extension that was established in 1991. Since the ALS and field data for A3 were collected
150 in 2005-2006, no silvicultural operations were carried out in the last 14 years.

151 In addition, some regional differences are evident in other site characteristics (see Table 1). In all
152 areas, most of the plots were located on mineral soils and the site type was mostly moderate or
153 poor, although, 3, 12 and 0 plots were located on fertile sites (*Oxalis-Myrtillus* type as defined by
154 Cajander 1949) in A1, A2 and A3, respectively. Scots pine was the dominant species in every
155 area, although some of the plots in A1 and A2 were dominated by Norway spruce (*Picea abies*
156 (L.) Karst) or by deciduous trees.

157

Field data

In A1, the field data was collected in summer 2017 from 47 plots, all of which had at least five pines with $\text{Dbh} \geq 16$ cm. From these square 30 x 30 m plots, Dbh, Cbh and H of every tree with $\text{Dbh} > 5$ cm was measured. The Cbh was defined as the height of the start of the lowest living branch in the living crown. Diameter at the height of 6 m (D6) was also measured from Scots pines with $\text{Dbh} \geq 16$ cm. Prior to the field measurements, canopy height models (CHM) were created for each plot and the location of every detected tree (laser tree) was determined. Therefore, during the field measurements it was only necessary to locate the non-detected (omission) trees: This was done by taking the distance and magnetic bearing to at least three correctly detected trees within a range of 2-10 m (Korpela et al. 2007).

A2 field data consisted of 66 plots measured in 2010 using a similar procedure as in A1. Plot sizes were 20 x 20 m, 25 x 25 m, or 30 x 30 m. The location, status (omission or laser tree), species, Dbh and H of each tree were determined or measured. Cbh and D6 were also measured to determine the proportion of sawlog-sized pines. In A3, 14 plots were measured in 2006 and the measurement scheme was similar to A1 and A2, although the trees were positioned in relation to GPS-positioned plot corners.

The volumes for the sawlog-sized pines, which are of primary interest in this study, were estimated by the model described in Laasasenaho (1982) that employs Dbh, D6 and H. In addition, Vlog was calculated by integrating a stem curve model (Laasasenaho's 1982) until the sawlog's fixed minimum diameter of 15 cm.

179 **ALS data**

180 All the inventory areas were scanned with different devices and scanning parameters (see Table
181 2). However, all the data were acquired in June or July during the leaf-on period of the deciduous
182 trees. Optech Titan provides multispectral ALS data, although only data from the channel with a
183 wavelength of 1064 nm was used in this study.

184

185 **Canopy height models**

186 We extracted the ALS data for plots using 5 m buffers to avoid edge effects in tree segmentation.
187 A canopy height model (CHM) was computed for each plot from partial CHMs that were
188 interpolated from triangulated irregular networks (TINs) computed from the ground echoes and
189 the echoes above 2, 5, 10, 15, 20 and 25 m height thresholds. Partial CHMs with larger threshold
190 values had empty pixels between crowns, while the lowest partial CHM represent the ground.
191 When these layers were stacked bottom up, no empty pixels remained in the final CHM as the
192 partial CHMs prevented the formation of falsely connected canopies above possibly empty
193 pixels. The step-by-step process is described by Isenburg (2014) and Khosravipour et al. (2014).
194 We used the following parameters: pixel size (stepsize) 0.333 m, diameter of the disc (sub-circle)
195 10 cm and maximum edge length of triangles (kill) 1.3 m.

196

197 **Segmentation and detection of individual trees**

198 The plot-level ITD process was implemented based on the final CHM (Hyyppä et al. 2001) using
199 the rLiDAR-package (Silva et al. 2017) created for *R* statistical computing environment (R Core
200 Team 2016). At the start, the CHM was low-pass filtered (Gaussian-filter; sigma value 0.6) to
201 eliminate additional false trees in the subsequent tree detection procedure. Next, the tree tops

were detected by searching local maxima (=treetops) from the CHM using the rLiDAR function *FindTreesCHM*. The crowns were then segmented using the local maxima and the rLiDAR function *ForestCAS*, which implements tree boundary delineation from the CHM. Since our main interest was in sawlog-sized pines, the segmentation function was limited to detect only trees > 8 m. Also, the expected maximum crown radius was fixed at 3.6 m, which was the maximum crown radius of pine trees observed in the earlier study by Korhonen et al. (2013). In addition, we only allowed pixels with a height at least half of the height of the tree to be included in the segments (exclusion-parameter). In the training data, the ratio between the crown base height and the tree height was approximately 2:3, which supported the increase of the exclusion-parameter from the default value (0.3 to 0.5). The segmentation was executed with the same parameters on each plot. The field-measured trees were linked to the segment they intersected, by using the known areas and shapes of the segments, and the known xy-locations of the trees. The tree list was reduced to reject falsely detected trees in instances where many of the field-measured trees were located inside one segment. First, all trees classified as omission trees during the field work were removed. This was done because the majority of the omission trees were located underneath ALS detected trees (e.g. understory spruce) and therefore they had a minimal effect on the ALS echo distribution of the segment. In segmentation, it is not guaranteed that all the nearby trees are correctly detected, so it was still possible that segments covering two or more field laser-trees existed. Because we wanted to study the accuracy of tree attribute imputations for cases without segmentation errors, all the remaining trees that shared the same segment with another tree were removed (Maltamo et al. 2012). Finally, all trees with the exception of Scots pines with field-measured Dbh ≥ 16 cm and

known D6 and Cbh information were removed from the tree lists that were eventually used in the modeling process (Table 3).

Tree and plot level ALS metrics

After segmentation, the locations and shapes of the polygons that describe the tree crowns were known and it was possible to extract the exact echoes that were located inside those polygons. This was done twice: initially for single & first of many (f), and then for single & last of many (l) echoes (Næsset 2002). The f/l echoes inside the segments were used to compute different ALS metrics for the tree in question. In addition, plot level ALS metrics were computed from all echoes that were located within the plot. Plot level ALS metrics were included since they provide information in regard to the neighbourhood of a tree (e.g. tree density, mean height).

The tree- and plot level ALS metrics describe the height- and intensity attributes and distributions of the echoes that had hit the polygon/plot, including maximums, minimums, means, medians, modes, variances, standard deviations, and the coefficients of variations. These were calculated separately from height- and intensity values of the echoes (Table 4). In addition, skewness and the kurtosis were calculated from the height- and intensity distributions. These ALS metrics were then linked to the corresponding field measured trees.

As it is known that intensities can vary remarkably between inventories (Hopkinson 2007, Korpela et al. 2010), the regional intensity distributions were examined before the modeling phase. Observed maximum and mean intensities were very different among the inventory areas (Table 5). Therefore, these intensities and the percentiles of intensities were not used later in the modeling. Only the relative metrics that describe kurtosis and skewness of the intensity distribution and the coefficient of variation of intensities proved to be similar between inventory areas and were accepted into the modeling phase.

249

250 **K-nn method**

251 In the k-nn imputations, a training dataset was used to estimate the attributes of interest in the
252 validation datasets. The k-nn imputation is based on the correlations between dependent and
253 independent variables: the values for the dependent variables of the validation trees are predicted
254 from the k nearest reference trees. These k trees are chosen by minimizing the distance calculated
255 from the values of the independent variables between the reference and validation trees.

256 We used the MSN (Most Similar Neighbor) distance metric in the k-nn imputation. It uses a
257 canonical correlation analysis based weighting matrix to select the most similar neighbors
258 (Moeur & Stage 1995). This matrix maximizes the correlation between dependent and
259 independent variables. In this study, the dependent variables were Dbh, H, Cbh, V and Vlog of
260 the selected pines. All the attributes for an individual validation tree were predicted
261 simultaneously from the same training trees using $k = 5$. The k-nn approach is especially useful
262 in cases where several parameters are estimated simultaneously for the same target, because it
263 guarantees that the predictions are logical and it retains the variance structure observed in the
264 training data (Eskelson et al., 2009). The k-nn imputations were performed with the yaImpute
265 package (Crookston & Finley 2008) in the R environment (R Core Team 2016).

266 The independent variables for the k-nn imputation of sawlog-sized pine attributes were selected
267 by manually testing hundreds of different ALS metric combinations including both tree and plot
268 level metrics. The aim was to include less than ten different ALS variables and to simultaneously
269 minimize the observed RMSE values for different attributes in the training (A1) data. We used
270 less than 10 independent variables to avoid overfitting (Packalen et al. 2012). The set with only
271 five height metrics proved to be quite accurate and the addition of further height metrics did not
272 improve the RMSE values. Nevertheless, we continued the selection process by testing the

relative intensities. The RMSE values decreased when two relative intensity metrics were added into the combination of predictors. Eventually, two combinations were accepted into the study: the “H-model”, which included five height based metrics, and the “I-model”, which included the same five height based metrics and two relative intensity metrics (Table 6).

Accuracy assessment

The accuracy assessment was made at the tree level using the relative RMSE (Eq. 1) and relative BIAS values (Eq. 2).

(1)
$$RMSE\% = \sqrt{\sum_{i=1}^n \frac{(x_i - y_i)^2}{n}} * \frac{100}{\bar{x}}$$

(2)
$$BIAS\% = \sum_{i=1}^n \frac{(x_i - y_i)}{n} * \frac{100}{\bar{x}}$$

where n is the number of trees in the dataset, x_i is the predicted value, y_i is the observed value and $\bar{x}$ is the measured mean in the dataset. Leave-one-out cross validation was used with the training data.

RESULTS

The tree level models were validated for both A2 and A3 (Table 7). The scatterplots of the H- and I-models were very similar inside the different areas, so for clarity only the scatterplots of H-model are presented in Fig. 2.

For Dbh, the I-model proved to be slightly more accurate in A1 (RMSE 13.5%) and in A2 (RMSE 14.8%), whereas the H-model was more accurate in A3 (RMSE 18.1%). In every area, the BIAS% was negative with the H-model and positive with the I-model. BIAS% values were the worst in A3. In A2, the imputation clearly overestimated Dbh at low observed values and there was a tendency to underestimation when observed values were > 25 cm (Fig. 2). In A3, more points were located above the xy-line.

In regard to tree height predictions, the difference between the RMSE% values of the models was negligible in the training data (3.17% vs 3.20%). The H-model was also more accurate in A2 (RMSE 5.88%), but not in A3 where the I-model produced better RMSE value of 6.24%. Both models underestimated tree heights in A2 (BIAS ca. -3%) and overestimated in A3 (BIAS ca. 2%). The scatterplots were somewhat similar between areas, though a few outliers were evident in A3.

For the Cbh, the I-model worked better in A1 and A3, whereas the H-model was more accurate in A2. In the training data (A1), a RMSE value of 13.3% was achieved. The relative RMSE values varied considerably in the validation areas: 15.3-16.1% in A2 and 18.3-22.4% in A3. The difference between the models was large especially in A3. In A2, the I-model resulted in clear underestimates (BIAS -6.1%), and both models produced overestimates in A3, with the relative bias of the H-model notably large (10.5%). This was also clearly seen in the Cbh scatterplot in A3. Moreover, the scattering of points in A3 was clearly larger than in A1 or A2.

For the prediction of V, the I-model was slightly more accurate in A1 (RMSE 29.3%) and this model was also the more accurate alternative in A2 (RMSE 35.4%), whereas the H-model was better in A3 (RMSE 39.1%). The H-model in A3 was the only prediction that yielded small underestimates (BIAS -0.5%) and the scattering of points was again more extensive in A3. The BIAS of I-model in A3 was rather large (6.8%).

The I-model was more accurate in predicting the volume of Vlog in A1 and A2. The lowest RMSE values observed were 38.2% in A1, 54.4% in A2 and 51.8% in A3. In this case, the BIAS% values were all positive excluding the H-model in A3 (BIAS -1.5%), i.e. Vlog was mainly overestimated in both validation areas, especially with I-model (BIAS 6.8% in A2 and 8.4% in A3). The underestimation of the H-model in A3 can be seen in the scatterplot, although, in this case the difference between A3 and A1/A2 scatterplots was not obvious.

DISCUSSION

Our aim in this study was to examine the accuracy of a k-nn model used for the prediction of sawlog-sized pines attributes when the model was applied in two separate inventory areas. As expected on the basis of earlier studies, the accuracies decreased for each attribute. The final accuracies were also clearly different between validation areas. Additionally, by focusing only on correctly detected pines, we ignored the effects of errors in tree species recognition or detection of individual trees (Falkowski et al. 2008). Therefore, our results may be too optimistic to be achieved in practice, unless the target stand covers only mature pines without overlapping crowns.

In the training data, the I-model with two intensity metrics proved to be the more accurate alternative for all tree attributes except height. Maltamo et al. (2009b) performed a similar study using k-nn and ALS material from the same inventory area (A3) and reported notably smaller RMSEs than our results from A1. However, they predicted all attributes separately, meaning that the most optimal predictors were specifically chosen for each attribute, and used 20-30 ALS predictors in each imputation without a rigorous cross-validation. The k-nn based MSN distance

metric was also used in Vauhkonen et al. (2010b) where tree level predictions for V produced RMSE values of 29.6-36.4%, i.e. comparable to our results.

Effects of transferring predictive models

The reduction in accuracies is caused by the differences in the ALS datasets and/or by the structural differences in trees between the inventory areas. As far as we know, the transferability of ALS based tree level models has not been studied earlier, so we cannot readily compare our results to other studies and therefore it is a challenge to establish whether the increase in RMSE% values is high or low. In the ABA study of Kotivuori et al. (2016), the relative increase in RMSE% of plot level V predictions varied between 2.9-42.9% (average on nine areas 17.4%) when using a cross-validated national model instead of a regional model. In our study the corresponding tree level values were A2: 19.4% (H-model) and 20.9% (I-model), and A3: 27.3% and 40.1%, respectively. However, this comparison is only indicative, and cannot answer whether the ITD or ABA models have better transferability in general. Overall, the RMSE% values associated with the different attributes in the validation areas are clearly larger compared to that usually achieved in training data (e.g. Maltamo et al. 2009b). The practical usefulness of these predictions depends on the demanded level of accuracy. For example, although the RMSE% values associated with H were approximately twice as high as the training data, the 6-7% RMSE value is still sufficiently low for practical applications. Also, the Dbh and Cbh predictions in A2 (RMSE ~ 15%) could be useful from a practical point of view.

However, the predictions were notably less accurate in both validation areas especially with the two volume related attributes, since the best observed relative RMSE values were with V and Vlog in A2 (35.4% and 54.4%, respectively) and A3 (39.1% and 51.8%, respectively). The accuracy of the V and Vlog predictions might not be adequate for practical applications, because

these are key attributes in the roundwood trade. On the other hand, when ITD and ABA have been compared at the plot level the attributes of the sawlog-sized proportion of diameter distribution have been predicted more accurately with ITD than ABA (Peuhkurinen et al. 2011).

In case of BIAS%, acceptable values are attribute-specific and depend on the intended usage of the predictions. If the predictions are employed in further models or estimations, they should be unbiased, because systematic errors accumulate and decrease the practical usefulness of the models. In our study, BIASes were in most cases below 10%, indicating rather low BIAS. Highest values were obtained for Vlog (1.5–8.4%) and Cbh (0.1–10.5%). However, e.g. for I-model in A2 the BIAS for Cbh was -6.1%, meaning that Cbh was systematically underestimated by approximately 67 cm. Considering the utilization of predicted Cbh (e.g. harvest scheduling), a bias of this magnitude would not severely decrease the usefulness of the predictions.

In the validation areas, the results of the models were not consistent: neither the H- nor the I-model was more accurate (in terms of RMSE%) for any attribute simultaneously in A2 and A3. The differences between the H- and I-models were mostly minor, although the I-model was clearly more accurate in the Cbh prediction in A3 (22.4% vs. 18.3%). This indicates that the inclusion of intensity metrics notably changed the most similar neighbors found by the k-nn algorithm. The intensity variables included in the models were coefficient of variation and skewness, which should not be as sensitive to scale differences as mean values or percentiles. The reasons why large variation or skewness in individual crown intensity distributions could be related to stem attributes are difficult to interpret. However, it is common that large canopy intensities are observed near the top of the crown, while small intensities occur near the edges where the foliage is sparse. Thus, the intensity metrics might be related to the crown area and shape, which were otherwise not represented in the models.

Interestingly, H predictions were underestimated in A2, whereas in A3 they were overestimated. A comparison of the inventory area specific averages of the 95th percentile of height metric derived from first echoes (H95TH_f) to the mean heights of the studied pines (see Table 3), displays a similar pattern: the H95TH_f underestimated H by 1.5 m, 2.2 m and 1.0 m in A1, A2 and A3, respectively. Therefore, it appears that compared to A1, the pulses penetrated deeper in A2 before the first returning echo was strong enough to be observed by the ALS device, and in vice versa A3. One explanation could be that the pine crowns were systematically sparser in A2, because it was scanned in June when the new shoots have not yet reached their full size (Hovi et al. 2016), while the other scans were made in July.

Nevertheless, Vlog was the only attribute for which more accurate results were obtained in A3 than in A2. Also, the differences in RMSE% values with other attributes were quite clearly in favor of A2. Therefore, it appears that the datasets of A1 and A2 were, in general, more similar to each other than the datasets of A1 and A3. Furthermore, it is possible that the trees were more similar between these areas, because silvicultural inactivity during the last 14 years in A3 may have led to different crown shapes in that area.

The effects of the ALS devices and scanning parameters used in this study cannot be excluded either, and they probably affected the results. For example, the regional mean pulse densities and the mean amount of first echoes per segment were in line with the results (A1: 13.2 pulses m⁻² & 243 echoes/crown; A2: 14.7 & 276; A3: 5.2 & 147). However, we were not able to evaluate and compare the real effects of the scanners and parameters with these datasets, thus we cannot be sure that the increase in the number of echoes per crown from 147 to 243 or 276, for example, made a significant difference.

The effects of the different ALS devices and scanning parameters have been studied frequently. As seen in Table 2, the regional ALS data acquisitions differed in almost every aspect. Næsset

(2009) observed significant differences between two scanning instruments, so presumably the three different instruments used in this study also produced different data compared to each other. In addition, flying altitude and pulse repetition frequency may affect the penetration of pulses and hence the height distribution of pulses (Hopkinson 2007) and proportion of pulses yielding multiple echoes (Næsset 2009). Keränen et al. (2016) observed that a narrower scanning angle led to slightly better accuracies of plot level V and H predictions, so the smaller scan angle in A3 may have had an effect here as well. Furthermore, the forest conditions in this study also varied between inventories, so we could not reliably estimate how much accuracies were decreased by the different ALS procedures, and how much by the differing tree structures in the training and validation datasets.

CONCLUSIONS

In this study, we examined whether k-nn models could be used to predict different tree attributes of mature Scots pine trees in separate ALS scanned inventory areas. Although the predicted and observed values showed strong correlations outside the training area (Fig. 2), the results were not satisfactory in terms of RMSE% or BIAS% values and may not be adequate for practical applications. The decrease in accuracy results from the use of different sensors and scan parameters, changes in forest structure with increasing distance, and the general difficulty of predicting stem attributes based on crown observations, which is exacerbated when the model is transferred to another region. Unfortunately, our research setup could not distinguish the contributions of these effects, but our results showed that the accuracy of ITD models may decrease considerably in this kind of realistic scenario.

Regardless, the transferability and the calibration of ALS models should be examined in more detail, with other characteristics, such as height of the lowest dead branch, quality reductions and other tree species, such as Norway spruce also considered. Rapidly increasing point density in ALS datasets makes ITD a realistic alternative in real world projects. At that point, knowledge with regard to model transferability and calibration may prove valuable.

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Table 1. Number of plots in each sub-class and description of site characteristics. Dominant species is derived from the species-specific total volumes.

Characteristic	Sub class	A1	A2	A3
	Number of plots	47	66	14
Soil type	Mineral soil	44	57	14
	Peatland	3	9	0
Site type	Fertile (OMT)	3	12	0
	Moderate (MT)	30	24	6
	Poor (VT)	14	30	5
	Xeric (CIT)	0	0	3
Dominant species	Scots pine	37	60	14
	Norway spruce	6	3	0
	Deciduous trees	4	3	0

* OMT = *Oxalis-Myrtillus* type, MT = *Myrtillus* type, VT = *Vaccinium* type, CIT = *Cladina* type

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Table 2. Scanning details of the inventory areas A1-A3.

Inventory area	A1	A2	A3
Scanning time (month/year)	7/2016	6/2009	7/2005
Sensor type	Optech Titan	Optech ALTM Gemini	Optech ALTM 3100
Flying altitude (m)	850	600	900
Scanning angle (°)	40	26	22
Pulse frequency (kHz)	250	100	100
Overlap (%)	55	55	35
Strip width on ground (m)	650	320	350
Mean pulse density (m ⁻²)	13.2	14.7	5.2
Echoes/crown (First)	243	276	147
Echoes/crown (Last)	74	90	75

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Table 3. Mean field measured attributes of the pines used in modelling. Standard deviations in parentheses. Dbh = diameter at breast height, D6 = diameter at the height of 6 m, H = height, Cbh = crown base height, V = stem volume and Vlog = theoretical sawlog volume.

Inventory area	A1	A2	A3	All
Number of trees	1071	420	317	1808
Dbh (cm)	24.8 (5.0)	23.1 (5.0)	24.6 (5.6)	24.3 (5.2)
D6 (cm)	19.7 (4.5)	16.9 (4.3)	19.3 (4.8)	19.0 (4.7)
H (m)	21.1 (3.6)	19.5 (3.6)	19.9 (3.9)	20.5 (3.7)
Cbh (m)	13.2 (3.5)	11.0 (3.1)	11.2 (3.2)	12.3 (3.5)
V (dm ³)	504.8 (310.3)	374.6 (259.5)	472.6 (277.6)	468.9 (298.2)
Vlog (dm ³)	416.7 (320.5)	276.0 (272.4)	386.9 (284.8)	378.8 (309.1)

Table 4. The main airborne laser scanning (ALS) metrics derived in this study. H=height, I=Intensity. In the percentiles $i = 5, 10, 15 \dots 80, 90, 95$ and 99.

ALS metric	Definition	Level
TotalReturns	Total number of returns	Tree
Total all return count		Plot
Total first return count		Plot
EWIDTH/NWIDTH	Tree crown width and depth	Tree
HMAX/IMAX	Maximum H/I	Tree & plot
HMIN/IMIN	Minimum H/I	Plot
HMEDIAN/IMEDIAN	Median H/I	Tree & plot
HMEAN/IMEAN	Mean H/I	Tree & plot
HSD/ISD	Standard deviation of H/I	Tree & plot
HCV/ICV	Coefficient of variation of H/I	Tree & plot
HMOD/IMOD	Mode of H/I	Tree & plot
H01TH/I01TH	1 st percentile of H/I	Plot
HiTH/IiTH	i^{th} percentile of H/I	Tree & plot
HVAR/IVAR	Variance of H/I	Tree & plot
HKUR/IKUR	Kurtosis of H/I	Tree & plot
HSKE/ISKE	Skewness of H/I	Tree & plot
CRR	Canopy relief ratio	Plot

Table 5. Means of intensity metrics (maximum, mean, kurtosis, skewness and coefficient of variation) by inventory areas; A1-A3. The _f denotes that the metric is derived from the first echoes only.

Intensity metric	A1	A2	A3	All
IMAX_f	18.5	113.2	50	46.1
IMEAN_f	7.6	54.5	27.4	22
IKUR_f	2.33	2.35	2.43	2.35
ISKE_f	0.22	-0.14	-0.31	0.04
ICV_f	57.2	49.9	43.8	53.1

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Table 6. Predictors used in k-nearest neighbor (k-nn) imputations. The H-model consists of the top five height metrics, whereas in the I-model all seven metrics were included.

Metric*	Definition
HMAX_f	Maximum height
H55TH_l	55 th percentile of height
H90TH_f	90 th percentile of height
HSD_p	Standard deviation of height
H15TH_p	15 th percentile of height
ICV_f	Coefficient of variation of intensity (only in I-model)
ISKE_p	Skewness of intensities (only in I-model)

* The letter at the end of metric describes the level and the echo type of the echoes used in calculations: f = first echoes at tree level, l = last echoes at tree level, p = all echoes at plot level.

Table 7. Root mean square error (RMSE%) and BIAS% values associated with the H and I models in the inventory areas (A1-A3). Training data (A1) was leave-one-out cross validated. Dbh = diameter at breast height, H = height, Cbh = crown base height, V = stem volume and Vlog = theoretical sawlog volume.

		A1		A2		A3	
		H	I	H	I	H	I
Dbh (cm)	RMSE%	13.81	13.48	14.98	14.79	18.08	18.42
	BIAS%	-0.05	0.15	-1.06	0.36	-1.56	2.70
H (m)	RMSE%	3.17	3.20	5.88	6.53	6.37	6.24
	BIAS%	0.04	-0.07	-3.03	-3.30	2.56	2.07
Cbh (m)	RMSE%	13.39	13.26	15.30	16.07	22.38	18.33
	BIAS%	-0.10	-0.13	0.12	-6.10	10.48	3.26
V (dm ³)	RMSE%	30.72	29.26	36.69	35.37	39.10	40.98
	BIAS%	0.10	0.42	0.47	1.96	-0.52	6.80
Vlog (dm ³)	RMSE%	39.76	38.16	56.24	54.39	51.76	53.95
	BIAS%	0.19	0.57	4.36	6.80	-1.53	8.40

Figure 1. The location of the airborne laser scanning (ALS) inventory areas (A1-A3). The field plots of A1 were located max. 20 km away from the point presented, whereas all the plots in A2 and A3 were located in compact clusters less than 3 km away from the points presented.

105x74mm (600 x 600 DPI)

Figure 2. Observed vs. predicted values of forest attributes in the inventory areas. Data only shown for H-model. Dbh = diameter at breast height, H = height, Cbh = crown base height, V = stem volume and Vlog = theoretical sawlog volume.

90x111mm (600 x 600 DPI)