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INDIVIDUAL TREE DETECTION AND AREA-BASED APPROACH IN RETRIEVAL OF FOREST INVENTORY CHARACTERISTICS FROM LOW-PULSE AIRBORNE LASER SCANNING DATA

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ABSTRACT

The two main approaches to derive forest information from small-footprint laser scanner data are the statistical area-based approach (ABA) and individual tree detection (ITD). In the present study we tested the accuracies of two ABA estimation methods, namely the k-nearest neighbour (k-NN) and a LASSO regression (LASSO) with ITD. In the estimation a practical low-pulse density (1.8/m^2) airborne laser scanning (ALS) dataset was used with same-date aerial photographs. The field data consisted of a test dataset of 97 plots and a modelling dataset of 236 plots. The modelling dataset included 20 plots that were used for bias calibration of forest characteristics calculated from ITD results. The root-mean-squared errors (RMSEs) for basal area, mean volume, mean height and mean diameter with ITD were 33.5%, 33.3%, 4.5% and 11.0% without calibration. The respective accuracies after calibration were 17.9%, 22.8%, 4.4% and 15.4%. With LASSO, the accuracies were 19.8%, 22.1%, 6.4% and 10.3% and with k-NN 24.6%, 25.8%, 9.1% and 13.5%. The ITD method gave as accurate results as did the ABAs when 20 plots were used in calibration.

1. INTRODUCTION

Forest management planning in Finland has been based on standwise field inventory. Currently, retrieval of stand characteristics is being replaced by airborne laser scanning (ALS)-based inventory. ALS is an accurate remote-sensing (RS) technique for forest inventory, providing relative accuracies for total volume ranging between 10% and 20% at the stand level in the Nordic countries (Næsset et al., 2004). The current data acquisition cost is comparable to that of traditional field measurement based inventory methods. ALS devices providing small-footprint diameters (10–30 cm) allow accurate height determination of the forest canopy (e.g. Næsset, 1997; Magnussen and Boudewyn, 1998; Magnussen et al., 1999; Means et al., 1999).

The two main approaches to derive forest information from small-footprint laser scanner data have been area-based approach (ABA) (Næsset, 2002) and individual tree detection (ITD) (Hyyppä and Inkinen, 1999). In the former method, statistics calculated from the laser point cloud are used as predictors and the retrieval of forest characteristics is typically based on parametric, nonparametric regression. For example, Næsset (2002), Lim et al. (2003) and Maltamo et al. (2006) showed that this approach produces highly reliable estimates of forest variables. In forest inventories in Scandinavia, species-specific information is needed for forest management planning growth projections and simulated bucking. Tree species-specific and timber assortment level estimates are investigated with ABA in, e.g., Packalén and Maltamo (2007) and Holopainen et al. (2010).

With the ITD method, individual trees are segmented from the laser point cloud, and tree level attributes are either determined straight from the point cloud or estimated based on various other ALS features that are extracted for the tree segments (e.g. Hyyppä and Inkinen, 1999; Persson et al., 2002; Leckie et al., 2003; Popescu et al., 2003; Vauhkonen et al., 2010). Forest structure and used algorithms have a major influence on tree detection accuracy in ITD (Kaartinen and Hyyppä, 2008). Tree level characteristics, such as species, diameter, height and volume are estimated with state-of-the-art ITD methods in recent studies by Maltamo et al. (2009), Korpela et al. (2010), Vauhkonen et al. (2010) and Yu et al. (2010).

The ABA is considered as a more cost-efficient approach than ITD, due to its lower pulse density at which it can operate accurately. However, it needs hundreds of expensively measured field plots, while the ITD method needs only a small ground truth dataset to calibrate ALS-based tree measurements (see Packalén et al., 2008). The ITD approach provides a means for assessing the true tree diameter and height distribution which are important in forest planning-related simulation and optimization, logging operation planning, and wood supply logistics. In ABA, forest mean characteristics are estimated to a sampling unit (e.g. grid cell or segment), but the stem distribution series would have to be predicted (e.g. Gobakken and Næsset, 2004; Maltamo et al., 2006; Packalén and Maltamo, 2008; Holopainen et al., 2010).

ABA and ITD inventories have been compared with different ALS datasets (e.g. Packalén et al., 2008), lower pulse density data is used for ABA than for ITD. However, it is important to test these methods with same ALS datasets and also with pulse densities that would be cost-efficient in practice. In the present study, we tested the accuracies of the two main ALS-based inventory methods, ITD and ABA, with practical low-pulse density ALS data combined with same-date aerial photographs. In all 97 plots were used for accuracy observation for basal area (BA), mean volume (Vol), mean height (Hg) and mean diameter (Dg). The accuracy of the plot Vol estimates was quantified for a subset of plots that were clear-cut and measured with a logging machine.

2. MATERIAL AND METHODS

2.1 Study area

The field data comprised 333 circular plots (r = 10 m), measured tree-by-tree, in an approximately 2000-ha managed forested area located in the vicinity of Evo, Finland (61.19° N, 25.11° E, Fig. 1). Field measurements were collected in 2007 and 2008. Sampling of the field plots was based on prestratification of existing stand inventory data to distribute plots over various site types, tree species and stand development classes. The plots were located with a GEOXM 2005 Global Positioning System (GPS) device (Trimble Navigation Ltd., Sunnyvale, CA, USA), and the locations were postprocessed with local base station data. The following variables were measured for trees with a diameter-at-breast height (dbh) larger than 5 cm: location, tree species, dbh, height, lower limit of living crown and crown width. The stem volumes were calculated with standard Finnish models (Laasasenaho, 1982). Plot-level estimates were obtained by summing the tree data.

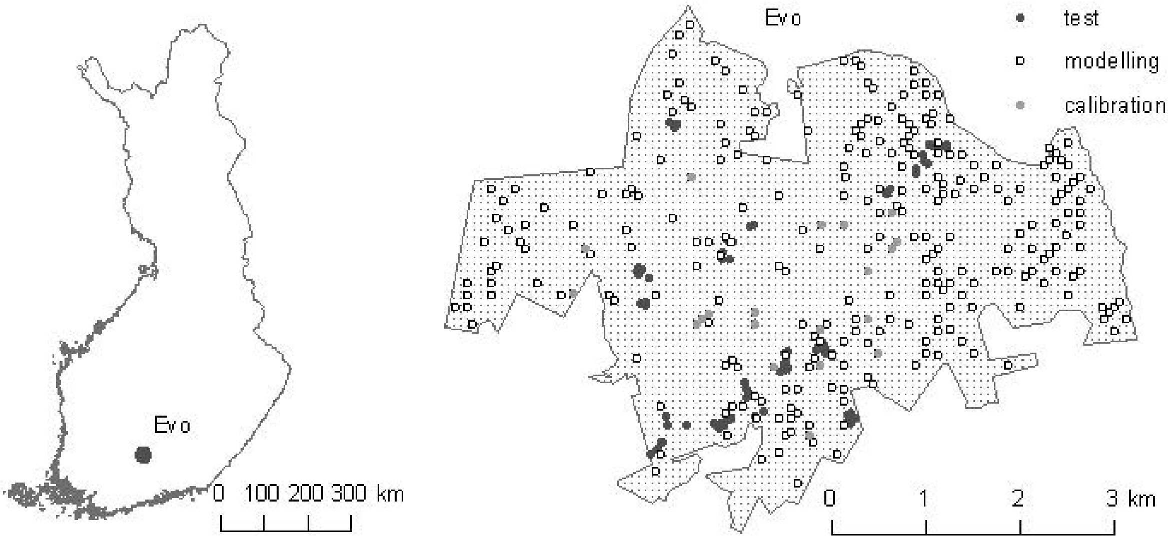

Figure 1. Location of the study area and the field plots

A subset (Table 1, Fig. 1) of 97 plots was selected for accuracy validation purposes (test data) from stand development class ranging from young thinning stand to the clear-cut stand. Forest characteristic estimation models used in ABAs were developed using the remaining 236 plots. From these 236 plots, 20 were selected to be used in ITD calibration. The selection criteria were based on BA range, according to the available stand register data. Vol estimation accuracies were also studied, using volumes measured with a logging machine as ground truth for 17 clear-cut plots.

Table 1. Range, mean and standard deviation of plot basal area (BA), mean volume (Vol), mean height (Hg) and mean diameter (Dg) in the test, modelling and calibration datasets.

Data set	n		min	max	mean	std
Test	97	BA, m^2ha^{-1}	5.5	43.4	26.7	6.7
Test	97	Vol, m^3ha^{-1}	47.5	530.5	245.9	84.9
Test	97	Hg, m	10.0	37.9	19.4	4.8
Test	97	Dg, cm	11.7	43.2	22.7	6.3
Modelling	236	BA, m^2ha^{-1}	6.1	59.6	22.8	9.7
Modelling	236	Vol, m^3ha^{-1}	54.9	691.7	208.7	118.6
Modelling	236	Hg, m	10.0	33.8	18.9	4.7
Modelling	236	Dg, cm	11.8	51.3	23.6	7.6
Calibration	20	BA, m^2ha^{-1}	7.9	45.5	27.8	9.8
Calibration	20	Vol, m^3ha^{-1}	65.9	575.1	293.4	149.4
Calibration	20	Hg, m	12.4	30.2	21.9	5.5
Calibration	20	Dg, cm	14.0	50.2	28.4	10.2

2.2 Remote-sensing materials and feature extraction for area-based methods

The ALS data were acquired in midsummer of 2006, using a Optech ALTM3100C-EA system (Optech Inc., Vaughan, Ontario, Canada); the flying altitude was 1900 m at a speed of 75 m/s, a half-angle of 14 degrees, a pulse rate of 70 kHz and a footprint diameter of 1.1 m. The density of the pulse echoes returned within the plots was 1.8/m^2 (only, first (F), intermediate or last (L); 1.3/m^2 if only the first returned pulses were considered). A digital terrain model (DTM) and, consequently, heights above ground level, were computed by the data provider. Same-date aerial colour-infrared photographs were taken with a Vexcel Ultracam digital camera (Vexcel Corporation, Boulder, CO, USA) with a ground resolution of 0.5 m.

Several statistical and textural features were extracted from the ALS data and aerial photographs. Firstly, the means and standard deviations of aerial photograph spectral values and ALS height and intensity were calculated. Secondly, Haralick textural features (Haralick et al., 1973; Haralick, 1979) were derived from spectral values and ALS height and intensity. Taking into account the spatial neighbourhood gives information complementing that contained in the spectral (or ALS height) values and their standard deviations. The Haralick textural features were computed for four directions: 0˚, 45˚, 90˚ and 135˚. For the above-mentioned features, the extraction window was 20 x 20 m, corresponding approximately to the size of the reference field plots. Thirdly, 'standard texture' features referring to a set of averages and standard deviations of spectral values, ALS heights (F returns) and intensities were calculated for a 32 x 32-pixel window from images rasterized to 0.5-m pixel size. Finally, height statistics for the F and L pulses were calculated: mean and maximum height (Hmean, Hmax), standard deviation and coefficient of variation of height (hstd, hcv), heights at which certain relative amounts of laser points had accumulated (h05-h95), as well as proportion of pulse returns below various relative heights (p05-p95). Only pulses exceeding a 2-m height limit were included to remove hits to ground vegetation and bushes. Penetration was calculated as proportion of laser pulses over 2 m in height compared to total amount of laser pulses. For the height statistics, the calculation unit was the actual circular field plot area. All features were standardized to a mean of 0 and standard deviation of 1.

2.3 Individual tree detection

The canopy height model (CHM) was computed as the difference between the digital surface model (DSM), representing the top of the crowns, and the DTM. The DSM of the crown was obtained by taking the highest value (Z-value) of all laser hits within each pixel. The value for missing pixels was obtained, using Delaunay triangulation and linear interpolation. Single-tree-based segmentations were performed on the CHM images, using a minimum curvature-based region detector (see Chandra and Sivaswamy, 2006). During the segmentation processes, the tree crown shape and location of individual trees were determined. First, the CHM was filtered by a Gaussian filter, using a standard deviation of 0.7 and bandwidth of five pixels. Then minimum curvatures were calculated. The CHM image was scaled by multiplying the image values with computed minimum curvature values, and local maxima were examined in a given 3 x 3-pixel neighbourhood and used as markers in the following marker-controlled watershed transformation for tree crown delineations. Each segment was considered to represent a single tree crown. Laser-based tree heights were obtained from the pixel with the highest CHM value within each segment.

The tree heights measured with ITD were calibrated with heights measured in the calibration field plots. A dbh was predicted for the trees, using the laser-based tree height and model developed by Kalliovirta and Tokola (2005) for boreal forest stands in southern Finland. Stem volumes were calculated using standard Finnish models (Laasasenaho, 1982) and for that the main tree species of the plots were assumed to be known. In ITD, plot-level forest characteristics were computed from the ALS-based tree heights, estimated diameters and volumes.

2.3.1 Calibration dataset for ITD

A calibration dataset (Table 1) of 20 plots was used to calibrate the bias in ITD and was selected, based on the BA information of a stand found from existing stand register data. The calibration functions used are presented below:

$BA_{cal} = 11.1 + 0.715 * BA_{pred}$ ($R^2 = 0.48$) (1)
$Vol_{cal} = 39.6 + 0.987 * Vol_{pred}$ ($R^2 = 0.71$) (2)
$Hg_{cal} = -0.0142 + 1.01 * Hg_{pred}$ ($R^2 = 0.97$) (3)
$Dg_{cal} = -7.04 + 1.32 * Dg_{pred}$ ($R^2 = 0.80$) (4)

where the subscript “cal” refers to the calibrated value and the subscript “pred” to the value calculated from trees detected in ITD.

2.4 ABA using k-NN

A reduced set of features was used in the k-NN estimation. In all, 11 features were selected among the 172 ALS- and aerial photograph-based features, using genetic algorithms (see Holopainen et al., 2008), and included percentages of points over 2 m in height (from the F and L pulses, separately, penetration), heights at which 30% of the laser pulses had accumulated (F and L pulse separately, h30), height at which 90% of the first pulses were accumulated (h90), mean height in a 32 x 32-pixel window (Hmean), angular second moment 45˚ of intensity (iasm), local homogeneity 90˚ of height (hidm), average NIR (nir20), std of NIR of 64 blocks within the 32 x 32-pixel window (nirstx) and std of G of 1024 blocks within the 32 x 32-pixel window (gstx).

The nonparametric estimation method was k-NN, which has long been used in Finnish RS-aided forest inventory applications (e.g. Kilkki and Päivinen, 1987; Tokola 1990, Muinonen and Tokola, 1990; Tomppo, 1991). The nearest neighbours were determined by calculating the Euclidean distances between the observations in the n-dimensional feature space. The number of nearest neighbours was set at five.

2.5 ABA using LASSO regression

The LASSO is a shrinkage and selection method for linear regression. It minimizes the usual sum of squared errors, with a bound on the sum of the absolute values of the coefficients. The LASSO method is described in further detail in Tibshirani (1996). LASSO models were estimated for Vol, BA, Hg and Dg, using R statistical software (R Development Core Team, 2007) and glmnet package (Friedman et al., 2010). In the modelling, a dataset of 236 plots was used (see Table 1). Several conversions were tested to turn non-linear regression into linear. In the final models, log-transformations were used. The bias stemming from non-linear conversion was calibrated by adding $\delta/2$ to the model before conversion back to the original scale. The parameters used in the models are presented in Table 2.

Table 2. Parameters used and parameter estimates for Vol, BA, Hg and Dg models, in which cor is the correlation between predicted and observed, %dev is deviation explained and δ/2 is the bias correction used.

Model Feature	ln(Vol) estimate	ln(BA) estimate	ln(Hg) estimate	ln(Dg) estimate
Int	4.387	1.926	0.333	1.026
$\ln(H_{max})$			0.654	
$\sqrt{H_{max}}$				0.348
$penetration^2$		-1.768		-0.257
$1/h_{20}$	-1.374		-0.219	
$\ln(h_{40})$				0.257
$\sqrt{h_{40}}$			0.165	
h_{50}^2		0.001		
$\ln(h_{90})$		0.415		
$\sqrt{h_{90}}$	0.691			
$\ln(p_{30})$	0.261			0.138
p_{30}^2		-0.494		
p_{40}^2	-2.726	-0.487		
$1/p_{90}$	-1.166			
cor	0.839	0.819	0.842	0.805
%dev	0.704	0.671	0.710	0.649
δ/2	0.133	0.091	0.020	0.028

2.6 Logging machine measurements

Data obtained from a logging machine in 17 plots (r = 10m) logged after the field measurements were used as reference data for Vol in separate observation. The logging machine gathered STM data according to the Standard for Forest Data and Communication (StanForD, 2006). An STM file includes data for each felled tree regarding the logging machine's position at the time of felling, stem diameters at 10-cm intervals from the felling height to the final bucking height, tree species, bucking parameters and bucked assortment volumes. The total tree height was estimated, based on the commercial timber height present in the STM file, using a model developed by Varjo (1995), and the volume of the treetop was added.

2.7 Accuracy observation

The accuracy of the estimated plot-level stand characteristics was observed by calculating the bias and root-mean-squared error (RMSE):

$$BIAS = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n}, \tag{7}$$

$$BIAS\% = 100 * \frac{BIAS}{\bar{y}}, \tag{8}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}, \quad (9)$$

$$RMSE\% = 100 * \frac{RMSE}{\bar{y}}, \quad (10)$$

where n is the number of plots, y_i the value estimated from the field data for plot i, $\hat{y}_i$ is the predicted value for plot i and $\bar{y}_i$ is the mean of the variable in the validation plots.

3. RESULTS

3.1 Accuracy of ITD, k-NN and LASSO methods

The accuracies of the ITD, calibrated ITD (ITD_c), k-NN and LASSO are presented in Table 3. The ITD calibrations for Vol and BA were effective, the bias in ITD_C was -4.9% for BA and 9.4% for Vol. Calibration of Hg and Dg did not improve the results. Without calibration, the ITD results were significantly poorer for BA and Vol.

Table 3. Accuracy of the characteristics estimated by ITD, ITD_C, LASSO and k-NN.

		BA, m^2/ha	Vol, m^3/ha	Hg, m	Dg, cm
BIAS	ITD	7.0	63.3	0.2	1.0
	ITD_C	-1.3	-23.1	-0.2	-1.7
	LASSO	0.6	1.9	0.0	-0.5
	k-NN	3.0	33.1	0.7	0.7
BIAS-%	ITD	26.1	25.7	0.9	4.5
	ITD_C	-4.9	-9.4	-0.8	-7.3
	LASSO	2.1	0.8	-0.3	-2.1
	k-NN	11.4	13.5	3.5	2.9
RMSE	ITD	9.0	81.9	0.9	2.5
	ITD_C	4.8	56.0	0.9	3.5
	LASSO	5.3	54.3	1.2	2.3
	k-NN	6.6	63.5	1.8	3.1
RMSE-%	ITD	33.5	33.3	4.5	11.0
	ITD_C	17.9	22.8	4.4	15.4
	LASSO	19.8	22.1	6.4	10.3
	k-NN	24.6	25.8	9.1	13.5

Vol was estimated most accurately with LASSO regression (RMSE 22.1%), although the RMSE with ITD_C was only slightly poorer (22.8%). The accuracy with k-NN was 25.8% and ITD 33.3%, the accuracies for BA were similar. The estimation accuracy (RMSE) varied from 4.4% to 9.1% for Hg and 10.3% to 15.4% for Dg. LASSO achieved the most accurate estimates for Dg (2.3 cm) and ITD_C was most accurate for prediction of Hg (0.9 m).

The observed vs. predicted values for BA, Vol, Hg and Dg are presented in Figure 2. From the figure, we can see the underestimation for BA and Vol with ITD. On the other hand, the ABAs tend to overestimate plots with low Vol or BA and underestimate high Vol plots.

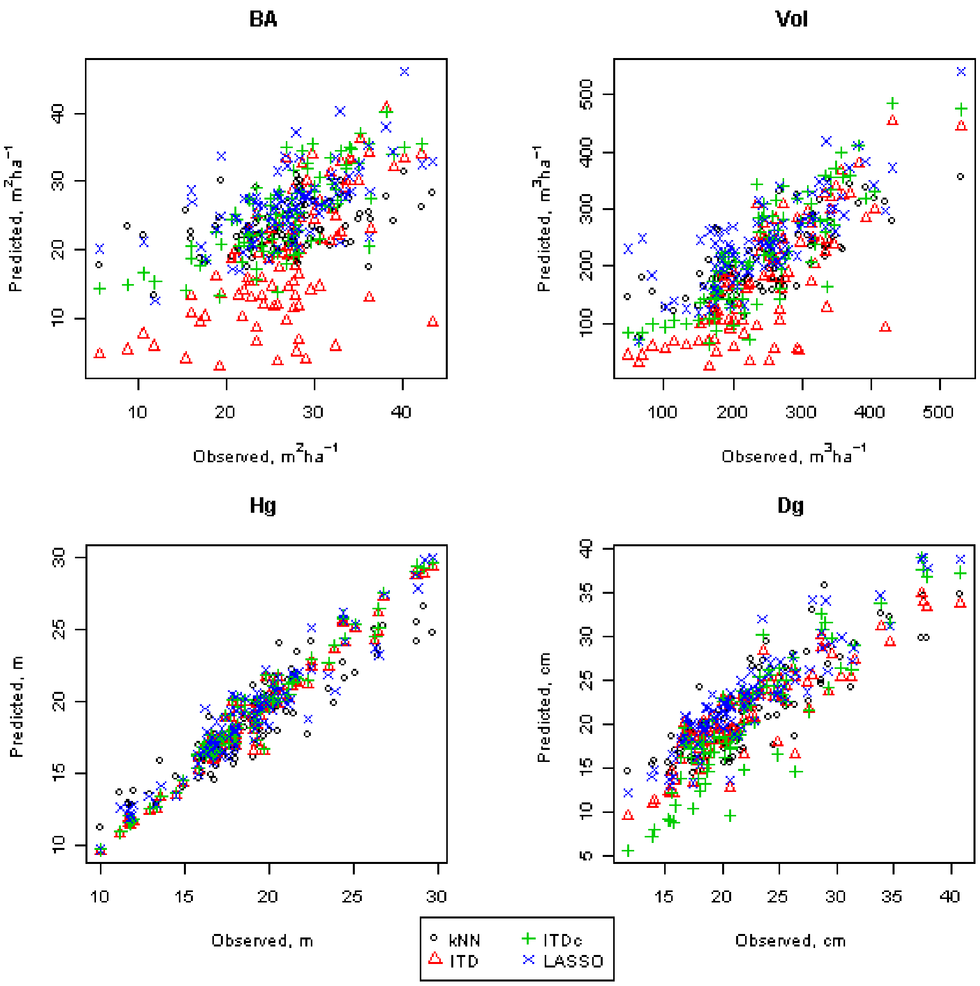

Figure 2. Observed vs. predicted stand characteristics.

3.2 Predicted volumes compared with logging machine measurements

In clear-cut plots where logging machine measurements were used as a ground truth (n = 17), the Vol estimation was as accurate with LASSO regression (12.9%) and ITD_C (13.0%) as with field measurements (13.2%) (Table 4). The magnitude of field measurement errors are seldom taken into account in this kind of study. The RMSE for Vol in the plot-wise field measurements was 38.1 m^3ha^{-1}, which is notable.

Table 4. Accuracy of the plot Vol.

	Field	ITD	ITD_C	LASSO	k-NN
BIAS, m^3/ha	-22.2	54.6	29.7	-16.4	13.2
BIAS-%	-7.7	18.9	10.3	-5.7	4.6
RMSE, m^3/ha	38.1	68.1	37.4	37.1	54.7
RMSE-%	13.2	23.6	13	12.9	19

4. DISCUSSION AND CONCLUSIONS

Standwise field inventories are being replaced by low-pulse density ALS forest inventories. In practice, higher pulse density is seen as being too costly. In the present study, we focused on comparing methods for carrying out ALS-based forest inventory with low-pulse density data combined with aerial photographs.

Our results showed that the ABA and ITD are each capable of producing estimates that are at par with traditional standwise field inventory (Poso, 1983; Haara and Korhonen, 2004; Saari and Kangas, 2005). The ITD method is as accurate as ABA, when a calibration dataset is used, especially to calibrate BA and Vol. Calibration plots were selected based on existing stand register data to cover a wide range in basal area. However, calibration data set had a larger average Dg than was in our test data. We assume that was the reason for increase in bias and RMSE after the calibration in Dg. From a practical stand point, our results achieved with ITD are promising and warrant further study. Although the LASSO regression method was more accurate than k-NN, we can conclude that the advantages of nonparametric estimation, such as k-NN, are better applicable for practical use, especially when species-specific characteristics are predicted.

Our study provides ALS data-based accuracy estimates for relatively heterogeneous area in southern Finland. In conclusion, we can say that the results were in line with other Finnish studies with low-pulse density data (e.g. Suvanto et al., 2005; Maltamo et al., 2006; Packalén and Maltamo, 2007; Packalén et al., 2008).

In the present study aerial photographs were used in conjunction with ALS data. The main advantage of including aerial photographs comes from improved accuracy of species-specific stand characteristics (Packalén and Maltamo, 2007). Although these characteristics were not estimated in this study, they will be required in any operational ALS-based forest inventory application.

Important differences among these methods include bias of the estimates and the amount of fieldwork needed. With low-pulse density data, the bias in the ITD method was notably greater in Vol and BA without calibration than in ABA. A solution is needed in ITD to better discriminate individual trees in multistorey and in dense stands. In the present study, the ITD method detected an average of 65% of the trees in a plot. Bias in Vol and BA was calibrated, using 20 field plots. Maltamo et al. (2004) used theoretical stem distribution functions to calibrate the bias in ITD. This method would be otherwise effective, but it requires larger sample plots for modelling. One interesting possibility for implementing ITD methodology in practical forest inventory is presented in Breidenbach et al. (2010) where so called “semi-ITD” is presented. In this method tree detection and the problem of biased ITD estimates are solved practically. Segmentation errors are taken into account by calculating volume for segments, not for individual trees. Because of the above-mentioned procedure, the bias of estimated volume is reduced.

The amount of fieldwork needed has a major negative effect on the cost-efficiency of inventory. The quality of ABA inventory is dependent on the quality and amount of fieldwork, since ITD requires fieldwork only to calibrate the estimates. ABA inventories are usually carried out with hundreds of reference plots, although the method may not require as much reference data if the measurements are directed carefully (e.g. Packalén et al., 2008).

We noted that the model developed by Kalliovirta and Tokola (2005), used in ITD to estimate dbh, was not accurate at the single-tree level. In the present dataset, the RMSE for a single tree's dbh was 40 mm. When both crown diameter and tree height were used, the RMSEs were even greater. A solution for this could be nonparametric estimation methods that have been recently utilized with promising results to estimate tree-level characteristics instead of regression modelling (e.g. Maltamo et al., 2009; Vauhkonen et al., 2010).

Accuracy in the field measurements was observed, using plots that were clear-cut and measured with a logging machine. This observation showed that field measurements include errors that should be noted and may influence the accuracy of the inventory methods evaluated and the models estimated. However, our comparisons were done in 17 mature stands and only Vol was considered, thus the results cannot be generalized to other stand development stages or other forest characteristics. The feasibility of using data collected by logging machines as field reference and modelling data should be investigated.

The results obtained here demonstrated that all ALS-based inventory methods can provide similar accuracies as those achieved with traditional field inventories. When low-density ALS data are used, bias in ITD must be calibrated. When costs of the field measurements should be minimized, ITD could be an effective option.

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