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ARTICLE

Effect of minimum diameter at breast height and standing dead wood field measurements on the accuracy of ALS-based forest inventory

Juha Keränen, Jussi Peuhkurinen, Petteri Packalen, and Matti Maltamo

Abstract: Where airborne laser scanning (ALS) measures the entire aboveground vegetation, the target of a stand-level forest inventory is usually the living tree stock above a given diameter but excluding standing dead trees. The aim here was to investigate the effects of varying field-measured minimum diameters (3–10 cm) and standing dead wood on ALS-based forest inventories. The characteristics considered in this case were volume, basal area, number of stems, mean diameter, and mean height for each species, as well as the total growing stock and the total aboveground biomass. The field data comprised measurements of all trees that were ≥3 cm at breast height (1.3 m) on 601 sample plots located in pine-dominated managed forests in eastern Finland. The results showed that the minimum diameter had a significant effect on the estimates obtained in young forests, for which the three smallest minimum diameter datasets (3, 4, and 5 cm) gave the most accurate estimates. Minimum diameter had no marked influence in the case of middle-aged or mature forests. The inclusion of standing dead trees did not have any effect on the estimates of living tree characteristics. The effect of minimum diameter is minor where large-area inventory applications are concerned; however, especially from a silvicultural point of a view, a minimum diameter of 3 cm should be employed in young forests, for which a large proportion of the tree stock usually consists of small trees, i.e., with diameters of <5 cm.

Key words: airborne laser scanning, *k*-NN, species-specific forest characteristics, diameter at breast height, field sample plot.

Résumé : Alors que le balayage laser aéroporté (BLA) mesure l'ensemble de la végétation au-dessus du sol, la cible d'un inventaire forestier à l'échelle du peuplement est généralement l'ensemble des arbres vivants dont le diamètre dépasse un seuil donné, mais à l'exclusion des arbres morts sur pied. L'objectif de cette étude était d'examiner les effets de différents diamètres minimum mesurés sur le terrain (3–10 cm) et du bois mort sur pied sur les inventaires forestiers réalisés au moyen du BLA. Les caractéristiques considérées dans ce cas étaient le volume, la surface terrière, le nombre de tiges, le diamètre moyen et la hauteur moyenne de chaque espèce ainsi que le volume total du matériel sur pied et la biomasse aérienne totale. Les données de terrain comprennent des mesures de tous les arbres ≥3 cm à hauteur de poitrine dans 601 parcelles d'échantillonnage établies dans des forêts aménagées dominées par les pins et situées dans l'est de la Finlande. Les résultats ont montré que le diamètre minimum avait un effet significatif sur les estimations obtenues dans les jeunes forêts, où les ensembles de données composés des trois plus petits diamètres minimum (3, 4, et 5 cm) ont donné les estimations les plus précises. Le diamètre minimum n'a pas eu d'influence marquée dans le cas des forêts d'âge moyen ou matures. L'inclusion des arbres morts sur pied n'a pas eu d'effet sur les estimations des caractéristiques des arbres vivants. L'effet du diamètre minimum est mineur lorsque l'inventaire est appliqué à une grande région, mais surtout d'un point de vue sylvicole, un diamètre minimum de 3 cm devrait être utilisé dans les jeunes forêts, où une grande partie du volume sur pied se compose généralement de petits arbres dont le diamètre est <5 cm. [Traduit par la Rédaction]

Mots-clés : balayage laser aéroporté, *k*-NN, caractéristiques forestières propres à chaque espèce, diamètre à hauteur de poitrine, placette d'inventaire terrain.

Introduction

The operational usefulness of remote sensing material was enhanced dramatically about 10–15 years ago when the airborne laser scanning (ALS) technique was developed further and became available for widespread use (Næsset 2002). The first large-scale, experimental, and ALS-based stand-level inventories, conducted in Norway in 2002 (Næsset 2004*a*) and in Finland in 2004 (Suvanto et al. 2005), adopted an area-based approach (ABA) in which stand attributes and ALS height distribution metrics were calculated for sample plots, yielding estimates for the stand characteristics of the total growing stock. Although this approach was directly suitable for operational use in Norway (see Næsset (2014)), it is often species-specific characteristics that are needed in Nordic forestry. Rapid technical progress was made, however, and the ABA method was further developed so that it provided species-specific information by combining ALS data with aerial images by means of nearest neighbor (NN) estimation (Packalén and Maltamo 2006, 2007, 2008). Thus, the first fully operational ALS-based inventory project in Finland was carried out in 2008 (Maltamo et al. 2011*b*). Meanwhile, the same method was being examined in a corresponding manner in northern America (Hudak et al. 2006, 2008; Jensen et al. 2006).

The predominant ALS-based inventory method in use nowadays is ABA, in which forest characteristics are determined at the sample plot (see Holmgren (2004) and Packalén and Maltamo (2006))

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or microstand (see van Aardt et al. (2006) and Pippuri et al. (2012)) level. ABA is especially applicable at the treatment stand level, as it provides information of relevance to forest planning systems. In Finland, this approach has mainly displaced the traditional field inventory method conducted by compartments (Maltamo and Packalén 2014), so that the Finnish Forest Centre has already generated up-to-date ALS-based forest property data covering ~4.3 million hectares of private forest (Suomen metsäkeskus (The Finnish Forest Centre) 2014), and the amount is continually growing.

The information contained in stand-level forest inventories includes characteristics such as mean height (*H*, m), mean diameter (*D*, cm), number of stems (*N*, $n\cdot ha^{-1}$), basal area (*G*, $m^2\cdot ha^{-1}$), volume (*V*, $m^3\cdot ha^{-1}$), and age (*T*, annum). The general need for information on stand characteristics in forestry has also been reflected in the development of ALS-based forest inventories (Popescu and Hauglin 2014). For instance, a growing interest has been shown in recent times in information on bioenergy content, as the use of biomass for energy production has increased, with a view to reduce man-made CO_2 emissions and comply with the carbon accounting requirements of the Kyoto protocol. As a consequence, ALS-based methods for the characterization of aboveground biomass (AGB) attributes have also been developed (Popescu 2007; Kotamaa et al. 2010; Næsset 2011). In the context of biomass assessment, probably the most promising international applications of ALS lie in sampling surveys related to REDD+ (see Ståhl et al. (2011) and Næsset et al. (2013)).

The obtainment of sufficient field reference material describing the variation in forest characteristics within an inventory area is a key aspect of remote sensing based forest inventories (see Gobakken and Næsset (2008, 2009)), and the need for this reference material to be accurate not only in terms of content, but also with respect to positioning accuracy is a relevant issue (Maltamo et al. 2011*b*). Accurate positioning makes it possible to combine field and remote sensing datasets (Gobakken and Næsset 2009). The acquisition of field data for an ALS-based inventory project nevertheless entails considerable costs, and research efforts have been devoted to developing strategies for selecting sample plots (Maltamo et al. 2011*a*) and optimizing their size (Gobakken and Næsset 2008) and number (Junttila et al. 2008) to minimize those costs. GPS positioning accuracy has also been examined in this context (Gobakken and Næsset 2008), and edge-tree correction for sample plots has been proposed in connection with ABA to ensure a better match between ALS and field data (Mascaro et al. 2011; Packalen et al. 2015).

One special issue regarding data content is the minimum stem diameter, i.e., the smallest tree to be included in the field data for a plot, as defined by its diameter at breast height (DBH, 1.3 m). The minimum diameter accepted in an inventory has varied in both practical and experimental situations. A minimum diameter of 5 cm has been employed in many Nordic studies (e.g., Suvanto et al. 2005; Packalén and Maltamo 2007; Holopainen et al. 2008), but Næsset (2004*b*) used a 10 cm limit in his field measurements, and Maltamo et al. (2015) settled for a minimum diameter of 4 cm. The minimum diameter has also varied between stand development classes, so that Næsset (2004*a*), for example, measured all trees over 4 cm in diameter on the sample plots located in young and middle-aged forests, whereas the limit was set at 10 cm in mature forests. The selection of a minimum diameter may also be dependent on the general structure of the forest, leading to larger values in North America, for instance, where Hawbaker et al. (2009) used a minimum diameter of 12.7 cm (5 inches) together with a distance limitation, and Woods et al. (2011) accepted all trees over 9.1 cm. It is only in short-rotation plantations with an even stand structure that all the trees are usually measured (Packalén et al. 2012). Despite the many previous studies focused on other aspects related to the field data used in ALS inventories, there have been no investigations into the optimal minimum diameter to be measured in the field, even though this can affect the costs of inventories and probably also their estimation accuracy, as detailed above.

Another issue related to minimum diameter is the fact that, in principle, ALS measures the entire aboveground vegetation, whereas the target of a stand-level forest inventory is usually the living tree stock above a given diameter limit, so that standing dead trees lie beyond the scope of the inventory. There are some studies in which the characteristics of standing dead trees have been modelled separately by ALS in the case of conservation areas (e.g., Pesonen et al. 2008; Bater et al. 2009), but they are not usually considered part of the tree stock, and in any case, dead trees are generally taken to comprise not only standing dead trees, but also fallen trees. Therefore, it is not usually possible to achieve a precise match between ALS and measurements of the tree stock in an inventory. This may constitute a considerable source of error, especially in young stands and stands with a naturally heterogeneous structure. Mismatching datasets probably have a significant effect on inventory results, especially in the case of sum characteristics of the tree stock such as total volume and total aboveground biomass, in which the relationship between the ALS findings and the tree stock is a straightforward one, whereas measures such as *D* and the *N* are, in any case, based more on statistical prediction. That is the reason why there are some cases (e.g., managed mature forests) in which the mismatching of the data (due to the minimum diameter limit or the presence of standing dead wood) has no significant effect. In addition, if a considerable part of the diameter distribution is absent from the training data used in NN-estimation due to the diameter limit, this may detract from the possibilities of predicting growth or determining the next silvicultural activity for the stand.

The main aim of this paper is to determine the effect of varying the minimum diameter when estimating plot-level, species-specific stand characteristics (*H*, *D*, *N*, *G*, and *V*) and total AGB by means of ALS and aerial photographs. In addition, an attempt will be made to determine the impact of the inclusion of field-measured standing dead wood in the above calculations. Stand characteristics were assessed using a similar NN-approach to that used in Finnish ALS-based stand-level inventories, so that the procedure involves the acquisition and calculation of both field and remote sensing data and estimation of the stand characteristics and AGB in the form of repeated simulations with separate training and validation data.

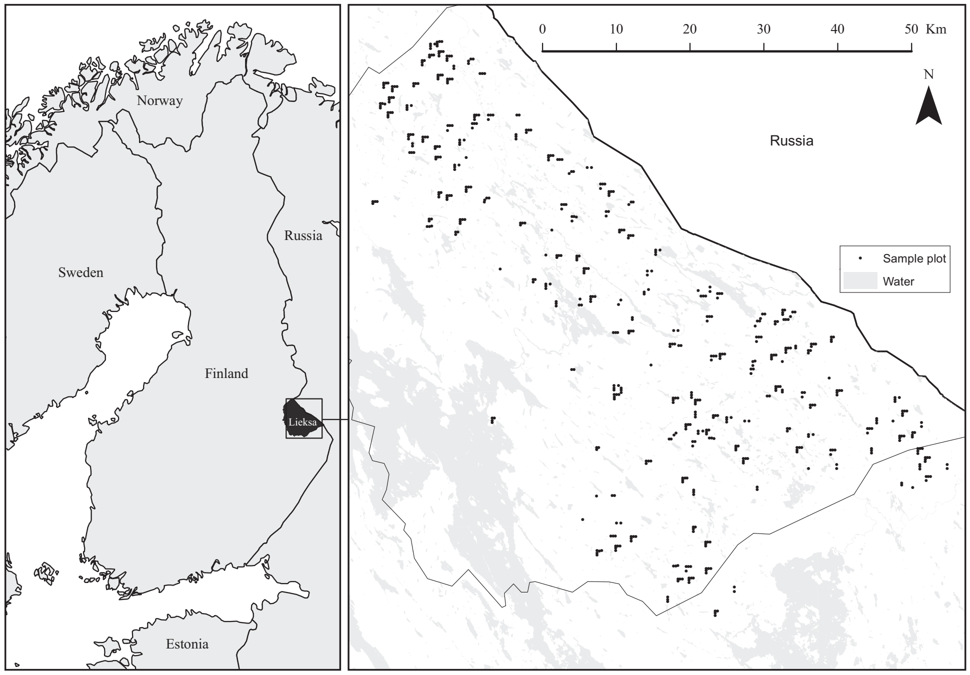
Materials and methods

Remote sensing data and metrics

The area concerned is located in the municipality of Lieksa in eastern Finland (63.19°N, 30.02°E) (Fig. 1), and the remote sensing material consists of ALS data and aerial images acquired to produce forest data for operational purposes. Leaf-on ALS data were collected between 13 June and 5 July 2012 using a Leica ALS60 laser scanning system. The laser scanner was calibrated once and placed in a Cessna 404 (OO-MAP) airplane. Trimble-operated, VRS base stations were used for GPS positioning, and the flight altitude was 1800 m above ground level, the flight speed was 62 $m\cdot s^{-1}$, and the scanning angle was ±20°. These settings resulted in a point density of 0.96 $measurements\cdot m^{-2}$ in the sample plots. The points were first classified as ground and nonground hits according to the approach described by Axelsson (2000), and the aboveground heights were then computed by triangulating the ground hits and subtracting the ground height from the ALS echoes. The ALS echo data were clipped according to the radius of the sample plot with Fusion (Fusion software, version 3.30, available from http://forsys.cfr.washington.edu/fusion/fusionlatest.html, accessed 12 January 2015) before calculation of the ALS metrics.

The ALS metrics to be used as predictor variables in the NN imputation were computed with the Fusion toolset's Cloudmetrics

Fig. 1. Location of the forest area studied and the sample plots.



program using all the echoes. Because a height limit of 2 m was used in the calculation, the echoes with height values of <2 m were ignored. This threshold value is commonly used in practical ALS-based forest inventories in Finland. Altogether, 70 ALS metrics were used in this work, as listed in Table 1. These are explained in detail in the Fusion software manual (available from http://forsys.cfr.washington.edu/fusion/fusionlatest.html).

The aerial images that constituted the second part of the remote-sensing data were collected during summer 2012 using an UltraCam D-camera placed in a Piper PA-31-350 Chieftain airplane (OH-PNX). The numerical metrics defined from the orthoimages using ArboLiDARtools included band-wise (near infrared (NIR), red, and green) means, standard deviations, histograms, and Haralick feature scheme values. The histogram schema was calculated from the normalized difference vegetation index (NDVI), NDVI2, and the gradients of the intensity images. NDVI and NDVI2 were calculated using eqs. 1 and 2:

$$\text{(1)} \qquad \text{NDVI} = \frac{(\text{NIR} - \text{red})}{(\text{NIR} + \text{red})}$$

and

$$\text{(2)} \qquad \text{NDVI2} = \frac{(\text{green} - \text{red})}{(\text{green} + \text{red})}$$

The gradient of the intensity image was calculated using Sobel convolution kernels (both horizontal and vertical), and the magnitude of the gradient, as used here, was calculated with eq. 3.

$$\text{(3)} \qquad G = \sqrt{G_x G_x + G_y G_y}$$

where G_x is the horizontal gradient and G_y is the vertical gradient. The descriptor for each target area contains four-bin histograms for the NDVI, NDVI2, and gradient values that lie within it. The Haralick schemas calculated from the NIR, NDVI, and NDVI2 images (Table 1) include the following expressions determined from the co-occurrence matrix: angular second moment, contrast, correlation, sum of squares, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measures of correlation, and maximal correlation coefficient (Haralick et al. 1973; Haralick 1979).

Field data

The field data, acquired during the summer of 2012, consisted of 601 prelocated, field-measured fixed-radius plots located in managed young, middle-aged, and mature forests. Sampling was based on a prestratification of the existing current forest inventory data, not only to rationalize the fieldwork by minimizing the time spent on moving between plots, but also especially to ensure a comprehensive set of field data representing the forests of the inventory area so as to enable proper estimation of the forest characteristics. To improve the efficiency of the fieldwork, the sample plots were clustered into groups of one to five plots. The centers of the plots were located with a Trimble GPS device using the GPS and GLONASS satellites. Over 50 positioning observations were collected with a frequency of 5 s, and the corrected locations of the plots were postprocessed by reference to the local VRS base station. This resulted in a computational accuracy of approximately 0.25 m both vertically and horizontally.

Field measurements were made within a 9 m radius (area, 254.5 m^2) on 543 plots and an 11 m radius (area, 380.1 m^2) on 58 plots. The wider radius was mainly designed for sparse stands in which N was relatively low. The field measurements consisted of general information (mineral soil or peatland, site fertility, etc.) and measurements of tally trees and sample trees. All trees with a DBH of at least 3 cm were taken into consideration, and the species, class (alive or dead), and DBH were determined for each. Up to three sample trees were measured for each species or species group: Scots pine (*Pinus sylvestris* L.; hereafter pine), Norway spruce (*Picea abies* (L.) Karst.; hereafter spruce), and deciduous trees, mainly birch (*Betula* sp.). The H and T of each sample tree were measured, and the tree H data were used to calibrate Veltheim's (1987) height models. The V of the trees were calculated using standard Finnish models (Laasasenaho 1982).

The field measurements formed the basis for calculating five plot-level characteristics for each species (pine, spruce, and decid-

Table 1. Remote sensing features calculated from the ALS data and aerial images.

Definition	Abbreviation
ALS data	
Maximum of point heights	LHMAX
Means of point heights and intensities, respectively	LHMEAN; LIMEAN
Standard deviations of point heights and intensities, respectively	LHSTD; LISTD
Variations of point heights and intensities, respectively	LHVAR; LIVAR
Coefficient of variations of point heights and intensities, respectively	LHCV; LICV
Interquartile distances of heights and intensities, respectively	LHIQD; LIIQD
Skewness of heights and intensities, respectively	LHSKEW; LISKEW
Kurtosis of heights and intensities, respectively	LHKURT; LIKURT
Mean absolute deviations of point heights and intensities, respectively	LHAAD; LIAAD
L-moments of heights and intensities, respectively	LHL1,…, LHL4; LIL1,…, LIL4
2nd L-moment ratios (CV) of point heights and intensities, respectively	LHLCOV; LILCOV
3rd L-moment ratios (coefficient of skewness) of point heights and intensities, respectively	LHLSKEW; LILSKEW
4th L-moment ratio (coefficient of kurtosis) of point heights and intensities, respectively	LHLKURT; LILKURT
Percentile values of point heights and intensities (1st, 5th, 10th,…, 90th, 95th, 99th)	LX01, LX05, LX10,…, LX90, LX95, LX99
% canopy cover at 2 m (first)	CCF2M
% canopy cover at 2 m (all)	CCA2M
(All returns above height break)/(total first returns) × 100	CCPAF2M
% canopy cover at mean canopy height (first)	CCFMEAN
% canopy cover at modal canopy height (first)	CCFMODE
% canopy cover at mean canopy height (all)	CCAMEAN
% canopy cover at modal canopy height (all)	CCAMODE
(All returns above mean)/(total first returns) × 100	CCPAFMEAN
(All returns above mode)/(total first returns) × 100	CCPAFMODE
Aerial image data	
Histogram schema values from NDVI, NDVI2, and intensity gradient images	RI_R12_01,…, RI_R12_12
Haralick features from near infrared (NIR) image	RI_HNIR_01,…, RI_HNIR_14
Means of the color channels (N, NIR; R, red; G, green)	RI_NMEAN, RI_RMEAN, RI_GMEAN
Standard deviations of the color channels (N, NIR; R, red; G, green)	RI_NSD, RI_RSD, RI_GSD
Haralick features from NDVI image	RN_HND1_01,…, RN_HND1_14
Mean of NDVI image	RN_NDMEAN
Standard deviation of NDVI image	RN_NDSD
Haralick features from NDVI2 image	HNDVI2_01,…, HNDVI2_14

Note: Prefixes: LH, point heights; LI, point intensities; LX, either point heights or point intensities; CC, canopy cover.

uous trees): *N*, *G*, *V*, *H*, and *D*. Species-specific stand characteristics were calculated using different minimum DBH values ranging from 3 to 10 cm at 1 cm intervals. The AGB calculations were based on the biomass models presented by Repola (2008, 2009, 2013). An example of mean and sum stand characteristics for the 3 cm and 10 cm minimum diameter classes is presented in Table 2.

Site fertility was determined at the plot level using the forest site classification system of Cajander (1926). The forest types were mainly (96%) mesic and subxeric (MT and VT, respectively). The plots were found to be dominated by Scots pine (~85%), with rather similar proportions of Norway spruce and deciduous trees (~7%). The plot datasets were also divided into development classes by reference to the *D* of the total growing stock, resulting in the following proportions: young (29.5%–43.8%), middle aged (44.9%–55.7%), and mature (11.3%–14.8%). The *D* thresholds for these development classes were those customarily employed in Finnish forestry practice: young forests, <16 cm; middle-aged forests, 16–22 cm; and mature forests, >22 cm.

The effect of standing dead wood on the estimated plot-level forest characteristics was assessed using corresponding material to that used in the case of living tree characteristics. The sample plot datasets in which the dead trees were included corresponded to those containing only living trees except for the fact that all of the trees measured in the field were included in the calculations of the variables. The remote sensing material was the same in both cases. The mean amount of standing dead wood in the whole dataset was 1.5 $m^3 \cdot ha^{-1}$ and the standard deviation was 5.9 $m^3 \cdot ha^{-1}$.

Selection of variables and the *k*-MSN method

The variable selection algorithm (VSSA) developed by Packalén et al. (2012) was used for selecting the remote sensing metrics for NN analysis. The set of candidate predictor variables included not only the original values for the remote sensing variables, but also the following transformations: the square root, natural logarithm, inverse, and second and third powers. The variables were selected based on 15 species-specific plot characteristics, with the number of predictor variables being set at 15. When selecting variables for AGB estimation, only the AGB was used as a response variable, and the number of variables to be selected was set at five. An in-depth explanation of the method is given in Packalén et al. (2012).

Simultaneous NN imputation of the plot-level characteristics was performed by the *k* most similar neighbor (*k*-MSN) method, as has been widely used in Finland (Muinonen et al. 2001; Maltamo et al. 2006; Packalén and Maltamo 2006, 2007; Vastaranta et al. 2011). This nonparametric method is a modification of the MSN distance metric developed by Moeur and Stage (1995) and employs canonical correlation analysis to produce a weight matrix for selecting the *k* nearest neighbors. The observations that were similar in terms of the predictor variables were determined for each sample plot, and a total of 15 forest characteristics (or 16 when standing dead trees were included) were imputed. This simultaneous imputation of plot-level characteristics by tree species was carried out using the yaImpute package (Crookston and Finley 2013) in the R environment (R Core Team 2015). The number of nearest neighbors was set at five, and the variance weighting msn2 method was used. The estimates for the target characteristics were determined as weighted averages of the five nearest neighbors. In the case of *G*, *V*, and *N*, the values were calculated as the sum of the tree species values for the characteristic concerned, whereas for *D* and *H*, the values were calculated by weighting the tree species values by reference to their *G*. A similar calculation procedure was followed by Packalén and Maltamo (2007), for example.

Table 2. Summary of reference plot data in the 3 cm and 10 cm minimum diameter classes.

		Range		Mean		SD	
Stratum	Characteristic	3 cm	10 cm	3 cm	10 cm	3 cm	10 cm
All	*H*	6.3–22.4	7.7–23.5	13.9	14.8	3.2	2.9
	D	8.2–32.3	10.9–34.3	16.8	18.3	4.2	3.7
	G	1.4–56.5	0.3–52.7	17.8	15.3	7.2	7.3
	V	11.0–511.3	1.2–493.9	127.0	116.2	66.0	67.3
	N	26–5109	26–1808	1530	684	827	304
	AGB	6.3–251.2	0.6–241.7	66.4	60.4	33.5	34.1
Scots pine	*H*	4.7–24.7	7.7–25.0	14.4	14.9	3.4	3.1
	D	5.1–43.8	10.4–43.8	17.8	18.6	4.7	4.1
	G	0–33.3	0–32.8	12.7	11.7	6.6	6.6
	V	0–315.3	0–315.3	94.8	90.0	58.2	58.7
	N	0–2751	0–1611	774	496	534	287
Norway spruce	*H*	2.1–21.2	7.2–21.9	9.4	13.2	4.4	3.0
	D	3.0–28.8	10.0–29.2	11.3	16.4	6.0	4.5
	G	0–31.5	0–30.3	2.3	1.8	4.2	3.9
	V	0–280.6	0–276.7	15.5	13.6	32.5	31.3
	N	0–3458	0–865	260	85	378	158
Deciduous trees	*H*	2.6–22.2	8.0–23.0	10.1	14.1	3.9	2.8
	D	3.0–29.1	10.0–33.4	9.9	15.1	5.1	4.1
	G	0–24.4	0–22.7	2.7	1.8	4.1	3.3
	V	0–216.8	0–206.2	16.7	12.7	29.2	26.3
	N	0–4283	0–1179	495	103	636	180

Note: *H*, mean height (m); *D*, mean diameter (cm); *G*, basal area ($m^2 \cdot ha^{-1}$); *V*, volume ($m^3 \cdot ha^{-1}$); *N*, number of stems ($n \cdot ha^{-1}$); AGB, aboveground biomass ($Mg \cdot ha^{-1}$); SD, standard deviation.

AGB estimation required procedures of two kinds. Firstly, *k*-MSN imputation was performed only for AGB that consisted of living trees, and then, it was also performed for AGB that included standing dead trees (AGB_{dead}). In other words, AGB_{dead} is the total AGB of standing trees above the given minimum diameter. The purpose of this examination using AGB_{dead} was to achieve a better description of the relation between ALS and total AGB than with an AGB figure derived only from living trees. To improve the reliability of the results, a simulation was used in which the calculation was repeated 100 times, the data having been split into training and validation datasets at the beginning of the simulation based on a stratification of the sample by development classes, in which there were always 400 sample plots in the training data and 201 sample plots in the validation data.

Performance assessment

The prediction error of NN imputation for the plot-level forest characteristics was assessed in terms of relative RMSE and bias (eqs. 4 and 5).

$$(4)\qquad \text{RMSE\%} = \left\{ \sum_{i=1}^{100} 100 \frac{\sqrt{\left[\sum_{i=1}^{n}(\hat{y}_i - y_i)^2\right] \Big/ n}}{\bar{y}_i} \right\} \Bigg/ 100$$

and

$$(5)\qquad \text{bias\%} = \left\{ \sum_{i=1}^{100} 100 \frac{\left[\sum_{i=1}^{n}(\hat{y}_i - y_i)\right] \Big/ n}{\bar{y}_i} \right\} \Bigg/ 100$$

where y is the observed value for the sample plot, $\hat{y}_i$ is the predicted value for sample plot simulation i, $\bar{y}_i$ is the true mean of the variables in the plot sample, and n is the number of plots in one sample. RMSE% and bias% were calculated separately for the training and validation datasets and also separately for the three stand development classes in both of these. In the case of the mean characteristics (*D* and *H*), only those sample plots that had observed and estimated values greater than zero were taken into consideration, whereas for all the other characteristics, all of the sample plots were included in the performance assessment. This meant that 17–21 plots for pine, 174–333 plots for spruce, and 109–299 plots for deciduous species were ignored when considering the calculation of the mean characteristics.

Results

Variable selection

In the case of 15 species-specific dependent variables, the selection process resulted in nine ALS metrics (four applying to height, four applying to intensity, and one applying to density) and six aerial image metrics (all textural metrics). When AGB alone was used as a dependent variable, the selection of predictor variables resulted in five ALS metrics (one height, one density, and three intensity metrics), whereas none of the aerial image metrics was selected.

Estimation of forest characteristics

The first imputation of forest characteristics was for living trees, after which the volume of standing dead trees was also included. The simulated results for the species-specific forest attributes on all the plots in the training and validation data are presented in Table 3. As pine was the dominant tree species, the accuracy achieved in the figures for pine and for the total growing stock can be treated as the primary results obtained here, in addition to which volume and biomass also have the expected close relationship to the ALS measurements when describing the total vegetation. There was not much difference in the accuracy of the volume estimates between the training and validation data when volume was considered (Table 3), which indicated that there was no overfitting associated with the NN approach. For example, the results for the total growing stock and for pine were more similar between the training and validation data overall, whereas a decline in accuracy was noticeable in the case of the minor species, especially with regard to the mean characteristics.

When the results are considered by diameter classes, it can be seen that the accuracy of *N* increased for Scots pine and the total

Table 3. The accuracy of total and species-specific attributes (RMSE%) in the training and validation data for all plots for the situation in which standing dead wood is excluded.

	Total					Scots pine					Norway spruce					Deciduous trees				
Minimum diameter	*D*	*H*	*N*	*G*	*V*	*D*	*H*	*N*	*G*	*V*	*D*	*H*	*N*	*G*	*V*	*D*	*H*	*N*	*G*	*V*
Training data																				
3 cm	14.7	8.9	37.9	22.7	25.1	16.0	9.2	51.7	37.6	40.4	50.6	43.9	120.4	134.8	158.1	49.1	34.5	89.2	96.3	113.9
4 cm	14.6	8.7	34.8	22.9	25.0	16.1	9.1	49.3	37.5	40.2	46.3	39.9	120.5	138.4	160.4	45.4	31.9	93.1	100.4	116.6
5 cm	14.2	8.5	33.2	23.4	25.2	15.8	8.9	47.9	37.6	40.3	43.4	37.1	123.1	141.2	161.6	41.0	28.1	102.7	106.9	121.1
6 cm	14.0	8.2	32.8	24.3	25.9	15.4	8.5	46.0	37.4	40.1	38.7	32.0	131.4	147.1	166.5	37.5	25.4	106.7	110.5	123.7
7 cm	13.8	8.0	32.2	25.1	26.6	15.3	8.5	43.9	37.5	40.2	35.6	28.6	137.7	153.6	171.5	33.5	22.5	111.9	116.0	128.2
8 cm	13.5	8.0	32.5	26.1	27.3	15.1	8.4	43.0	37.8	40.4	31.9	24.9	148.2	162.7	179.7	31.2	20.4	119.0	125.6	137.6
9 cm	13.2	7.8	33.2	27.2	28.1	14.7	8.3	42.1	37.7	40.2	28.7	22.1	151.8	166.1	182.3	27.6	17.9	130.5	135.2	146.2
10 cm	12.9	7.7	34.4	28.8	29.5	14.2	8.1	42.1	38.2	40.5	26.8	19.9	161.5	174.5	189.4	26.2	16.8	135.5	141.2	151.0
Validation data																				
3 cm	15.6	10.2	37.5	22.4	25.2	17.9	11.4	52.8	37.7	40.5	52.1	46.9	115.6	133.6	156.3	50.5	38.3	88.7	96.5	113.8
4 cm	15.4	10.3	34.1	22.5	25.2	17.6	11.2	49.9	37.4	40.2	49.5	44.5	117.3	133.5	155.0	48.7	37.2	91.3	100.0	116.3
5 cm	15.5	10.2	32.3	22.8	25.4	17.5	11.1	47.8	37.3	40.1	47.6	43.4	120.2	137.9	158.6	46.1	36.2	95.8	103.2	118.1
6 cm	15.4	10.3	30.8	23.1	25.6	17.3	11.0	46.2	37.6	40.4	46.5	42.5	125.7	142.8	162.1	44.6	36.7	102.7	108.9	122.6
7 cm	15.3	10.5	30.2	23.5	25.8	16.8	10.8	44.3	37.8	40.5	45.8	42.2	129.0	145.0	163.0	44.9	38.1	108.3	114.7	127.5
8 cm	15.2	10.7	29.4	23.8	26.2	17.1	10.9	42.5	37.4	40.3	45.8	42.7	134.5	147.3	164.3	46.2	40.7	109.8	115.3	126.8
9 cm	15.2	10.9	29.8	24.7	26.6	16.4	10.6	42.5	38.1	40.4	45.9	43.2	142.1	152.6	167.4	46.4	41.5	116.4	121.9	132.3
10 cm	15.2	11.2	29.9	25.2	26.9	16.0	10.6	42.0	38.3	40.7	45.6	43.4	143.4	154.7	169.2	46.6	42.6	122.5	130.3	140.9

Note: *D*, mean diameter (cm); *H*, mean height (m); *N*, number of stems ($n \cdot ha^{-1}$); *G*, basal area ($m^2 \cdot ha^{-1}$); *V*, volume ($m^3 \cdot ha^{-1}$).

Table 4. Accuracy of total and Scots pine volumes (RMSE%) in the validation data for the development classes, with the volume (*V*, $m^3 \cdot ha^{-1}$) of standing dead trees excluded or included.

	Standing dead trees excluded						Standing dead trees included					
	Young		Middle aged		Mature		Young		Middle aged		Mature	
Minimum diameter	Total	Pine	Total	Pine	Total	Pine	Total	Pine	Total	Pine	Total	Pine
3 cm	26.8	45.6	20.9	36.9	28.0	37.2	27.1	45.2	20.8	36.3	27.6	38.0
4 cm	27.6	46.0	20.8	36.5	28.0	36.7	26.9	45.6	20.6	36.6	27.4	37.2
5 cm	28.6	47.5	20.7	36.0	28.3	36.8	28.3	47.9	20.6	36.0	27.9	37.1
6 cm	29.5	49.2	20.7	36.1	28.0	36.7	29.2	49.4	20.5	36.7	27.1	36.7
7 cm	29.6	47.5	21.4	37.4	28.3	36.3	29.7	47.3	21.3	37.4	28.3	37.4
8 cm	31.6	48.1	21.1	37.2	29.2	36.1	32.4	49.9	21.3	37.8	28.0	36.0
9 cm	34.0	49.9	21.7	37.2	28.4	36.5	33.2	51.2	21.6	36.4	28.6	36.4
10 cm	36.1	51.6	22.2	37.5	28.3	37.2	36.4	51.1	22.2	37.9	27.9	37.5

Note: Validation data, $n = 201$.

Table 5. Accuracy (RMSE%) of AGB estimation for all plots in the training data and in various parts of the validation data, with standing dead trees excluded or included.

	AGB standing dead trees excluded					AGB (AGB_{dead}) standing dead trees included				
		Validation data $n = 201$					Validation data $n = 201$			
Minimum diameter	Training data $n = 400$	All	Young	Middle aged	Mature	Training data $n = 400$	All	Young	Middle aged	Mature
3 cm	25.0	23.6	23.7	21.0	25.8	23.7 (24.8)	23.4 (24.4)	23.4 (23.9)	21.1 (22.3)	25.0 (25.7)
4 cm	24.9	23.9	24.8	21.4	25.1	23.8 (24.8)	23.9 (25.0)	24.2 (25.0)	20.9 (22.2)	26.6 (27.2)
5 cm	25.4	24.4	25.3	21.2	27.0	55.7 (56.5)	56.4 (57.3)	76.1 (77.3)	45.5 (46.5)	53.6 (54.3)
6 cm	25.9	24.1	26.7	20.9	25.8	24.2 (25.1)	24.2 (25.2)	26.2 (26.8)	21.3 (22.5)	25.6 (26.3)
7 cm	25.9	24.7	28.2	21.4	26.4	24.7 (25.6)	24.8 (25.7)	28.1 (28.8)	21.1 (22.2)	27.1 (27.9)
8 cm	26.1	25.2	30.9	21.6	26.5	24.9 (25.8)	25.2 (26.0)	31.2 (31.8)	21.2 (21.8)	26.6 (27.9)
9 cm	27.0	25.9	34.7	22.0	26.0	25.4 (26.3)	25.7 (26.4)	34.6 (35.1)	21.7 (22.3)	26.1 (27.0)
10 cm	28.1	27.1	39.0	22.9	27.2	26.6 (27.4)	26.8 (27.7)	38.9 (39.4)	22.5 (23.1)	27.3 (28.6)

Note: AGB_{dead} refers to the combined aboveground biomass of living and standing dead trees (values in parentheses).

growing stock (see Table 3), most probably because of the powerful averaging effect of this characteristic, as extreme values diminish when the smallest diameter classes are excluded. The other notable result is the minor decline in the accuracy of *V* and *G* for the total growing stock in the training and validation data (Table 3). This led us to take a closer look at the total growing stock and pine volumes by stand development classes (Table 4), even though these results had also been calculated for the other characteristics (data not shown). Results that include standing dead trees can also be seen in Table 4.

Examining the volume predictions by stand development classes, it can be seen that an increase in the minimum diameter in the case of young forests makes the results for both the total growing stock and pine less precise, whereas no such trend exists in the other development classes. Alternatively, when the standing dead tree volume was added to the imputation of the species-specific characteristics, the estimation accuracies became similar to those of the alternatives without standing dead trees. Likewise, the inclusion of standing dead trees did not lead to any dramatic differences in accuracy between the training and validation data.

The accuracy of the volume estimates for standing dead trees was always rather poor, i.e., an RMSE% of 380% for the whole validation dataset, with the lowest RMSE% being 289% in the mature stands, in which all trees with a DBH of ≥4 cm were measured. In addition to the RMSE% values, the bias was also calculated for all the forest characteristics (data not presented). These values varied greatly between the characteristics, but the level of relative bias was generally lower than 10%. Some of the variables were occasionally statistically significantly biased in terms of the *t* test, especially in the case of minor species.

The results of AGB estimation are presented in Table 5. The results obtained with the training data were more or less identical in both imputation alternatives, with and without standing dead trees, whereas those for the validation data followed the figures for the volume of the total growing stock, so that standing dead trees did not have any notable effect and the predictions for young forests declined in accuracy as the minimum diameter increased. There was also a slight corresponding trend in the relation between the entire dataset and mature forests.

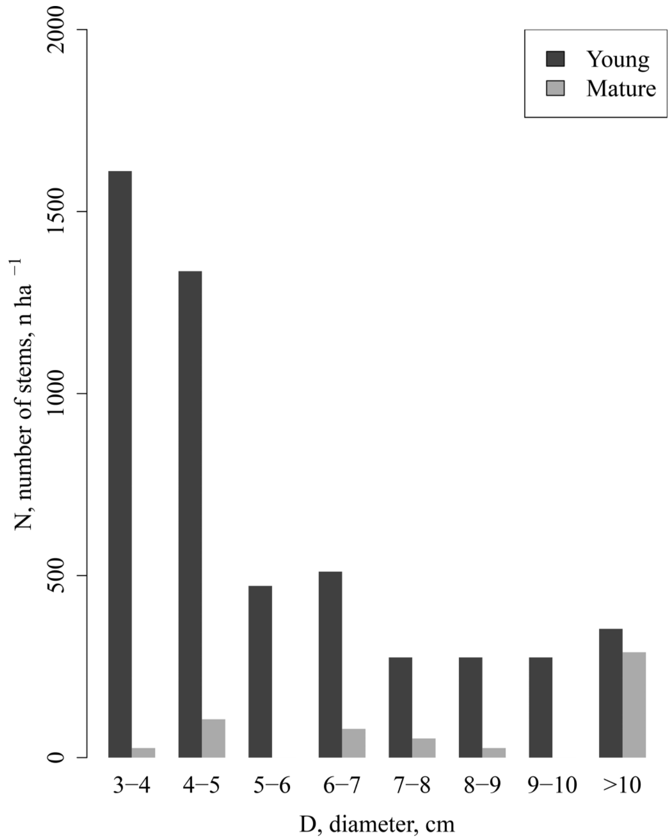
Discussion and conclusions

We examined here the effect of varying the minimum tree diameter and the inclusion of standing dead trees in the calculations on the accuracy of estimates for total growing stock and species-specific stand attributes and AGB. Although the effect of dead trees was minor, an increase in the minimum diameter reduced the accuracy of *V* and AGB prediction, especially in young forests. In general, differences in accuracy were already observed between adjacent minimum diameter classes, and the variation in accuracy was similarly high with different species within the development classes and between development classes within the same species. The variation in accuracy was smaller for the dominant species, pine, than for spruce or the deciduous trees.

There was a noticeable difference in accuracy between the development classes in this study, the greatest accuracy being achieved in the middle-aged forests, for which the effect of varying the diameter limit was also minimal. We similarly obtained highly accurate results in young forests when a minimum diameter below 5 cm was used, but the accuracy deteriorated dramatically at larger minimum diameters. On the other hand, the results achieved in the mature forests were somewhat better, on average, than the results achieved in the young forests. The results for the total volume of growing stock were better in the middle-aged forests than in the other development classes, probably because these forests had been intensively managed and the trees mainly had a quite large DBH, with the numbers of stems with a smaller DBH being relatively low due to thinning and advance clearing. The accurate results recorded in young and middle-aged forests are, in general, justified by the fact that they have practically always been artificially regenerated and intensively managed, and they account for the majority of the inventory area. Mature forests also include unmanaged stands with a natural forest structure, which exhibit more variation in forest characteristics, thus reducing the accuracy of estimation, but it is also the case that there were only a small number of such stands in the training data. The accuracy of the results is comparable with that reported in other studies employing similar material and calculation procedures (e.g., Maltamo et al. 2009, 2015; Wallenius et al. 2012).

The calculations were performed here simultaneously for all of the species-specific characteristics, although we were mostly interested in the *V* estimates. Our aim, of course, was to mimic practical forest inventory applications, and if we had only considered *V* this would have led to accuracy levels that were too optimistic. On the other hand, we also considered total AGB values, as in REDD+ applications, so that our approaches and results had to be applicable to large-area inventories. The effect of increasing the minimum diameter was, in general, rather small, but it was still highly important for young forests, showing that a small minimum diameter is needed to obtain a better match between the ALS data and the field plots. On the other hand, minimum diameter had only a slight effect on the AGB values for the whole dataset, so that it may not be of any importance for practical applications.

Fig. 2. Example of diameter distributions in two sample plots, one in a young forest and the other in a mature forest.



In addition to the better match between ALS and the field measurements, the background to the use of a smaller minimum diameter in young forests includes the fact that there are usually a large number of small-diameter trees (3–5 cm), whereas this number is lower in more mature forests. This issue can be illustrated by looking at sample diameter distributions from young forests (nearly 3000 stems·ha^{-1} between 3 and 5 cm) and mature forests (about 150 stems·ha^{-1} in the same range as the young forests). The overall stem density was 5100 stems·ha^{-1} in the young forests and 600 stems·ha^{-1} in the mature forests (Fig. 2).

We have considered here the measurement of trees with a DBH of 3 cm or larger, whereas the measurement of all trees with a height of ≥1.3 m would be a far more demanding task, and the resulting information on small trees would probably be untrustworthy and, therefore, useless for practical purposes. The National Forest Inventory of Finland (Korhonen et al. 2013) has produced information on the diameter distributions of forest trees for the operating areas of the individual forest centre. In northern Karelia, where the present area was located, 56% of all stems had a DBH between 0 and 2 cm when all the development classes were considered, whereupon it was the deciduous trees that were dominant. In terms of total volume, this implies that 0.8% of that volume consists of trees with a DBH of 0–2 cm. It is also worth noting that previous inspections had included all of the development classes and also seedling stands, which were not considered here.

The results concerning young forests have already been implemented in practical forest inventories performed by the Finnish Forest Centre, for which a 3 cm minimum diameter was used in the young forests but a 5 cm minimum diameter was used in the more mature forests. On the other hand, the minimum diameter limit cannot be increased too much, because some trees of economic value (e.g., as pulp wood) would then be excluded from the inventory. The principal aim of using a smaller minimum diameter in young forests is to improve the accuracy of the estimates needed for determining the next forest management, i.e., the first thinning. This can be explained by the fact that the smaller the trees measured on a sample plot are, the more accurate the species-specific variables are. Also, the diameter distribution (see Fig. 2) will then be more realistic and not be truncated. The total growing stock, which finally defines the need for forestry operations, is formulated through the sum of the species-specific estimates.

The feasibility of nonparametric methods for the estimation of ALS-based forest characteristics has already been demonstrated in previous studies (e.g., Packalén and Maltamo 2007; Maltamo et al. 2009, 2015; Vastaranta et al. 2012), and this is nowadays one of the main methods used for estimating the characteristics of the total growing stock and individual species in boreal forest inventories (see Maltamo et al. (2011*b*) and Turunen et al. (2012)). This study has dealt with variations in the minimum diameter as measured in the field, a topic which has not previously been considered. Earlier work has been concentrated on improving the accuracy of estimates by selecting the appropriate measurement and calculation methods (e.g., Næsset 2002; Gobakken and Næsset 2008; Junttila et al. 2008; Maltamo et al. 2015), and other possible sources of estimation error have also been explored (e.g., Næsset 2005; 2009; Villikka et al. 2012). The selection of variables for the NN method has also proved to be a demanding task, because the feature space of available variables increases in the case of remote sensing (e.g., Packalén et al. 2012).

The estimation of standing dead tree volume was also considered, and it was concluded that these trees did not have any effect on the accuracy of estimation of the living tree strata. The accuracy of the present estimates of standing dead tree volume was more or less parallel to that reported in existing dead tree studies. Maltamo et al. (2014), for example, reported a RMSE% of 244.8% for standing dead trees, whereas the corresponding value obtained here was 380%. The poor estimation accuracy is due to the small number of standing dead trees in managed forests (1.5 $m^3 \cdot ha^{-1}$). From a forestry inventory point of view, the measurement of standing dead trees is mostly justified to eliminate possible outliers in the modelling phase. When notable variation between sample plots occurs in the number of standing dead trees, the plots containing more such trees may have a bias effect on the model for living tree attributes. By collecting information on standing dead wood, these plots can easily be traced and, if necessary, left out of the model.

In conclusion, ALS has been in use for practical forest inventory purposes for about 10 years, and the minimum DBH measured in the field has varied during that time. Although this variation in minimum DBH can have an effect on the accuracy of the resulting estimates, it has not been studied until now. Our analysis of the effect of varying DBH on estimates of traditional stand characteristics and AGB indicates a significant relationship between the accuracy of the results and the minimum DBH, lending support to the use of a smaller minimum DBH in young forests. The inclusion of standing dead trees in field measurements or estimates did not have any significant effect on the accuracy in this area, for which the amount of standing dead wood was relatively low. In some other areas, however, for which standing dead trees are more common, it may have a larger effect. It is thus recommended that standing dead trees should be included in field measurements.

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