The comparison of airborne laser scanning-based probability layers as auxiliary information for assessing coarse woody debris

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Abstract

During the last 15 years the assessment of biodiversity has become more important in forestry. Coarse woody debris (CWD) has been recognized as one of the strongest indicators of forest biodiversity and the assessment of it has been emphasized in the development of new inventory methods for sparse populations. In this study, the use of airborne laser scanning (ALS)-based probability layers in guiding the sampling-based field inventory of CWD was tested on a field area of 286 hectares. The auxiliary information was used by implementing point proportional to size (PPS) sampling in the selection of the first stage sample units in simple random sampling (SRS) and adaptive cluster sampling (ACS). The sampling methods were compared by means of the accuracy of the mean volume (m^3ha^{-1}) estimates for CWD with fixed input effort specified as field working hours. The accuracy of CWD volume estimates with PPS and PPS+ACS, where ALS-derived probability layers were utilized, was higher than the accuracy of SRS and ACS. Thus, this paper introduces new possibilities for making the inventory of CWD more efficient.

Keywords: Airborne laser scanning, Coarse woody debris, Probability layers

1. Introduction

In large-scale forest inventories, information about the forest characteristics is often acquired using sampling, since an inventory of the total population is often expensive or even impossible. During recent decades, increasing attention has been paid to forest biodiversity on all its levels, from the variety of ecosystems to richness in species and genes. Coarse woody debris (CWD) has been recognized to be one of the most important indicators of forest biodiversity, since a high proportion of rare and specialised species is dependent on it (e.g. Siitonen 2001; Karjalainen and Kuuluvainen 2002). Traditional methods of measuring and modelling these attributes have been expensive and of low accuracy, because dead trees are rare and their existence is clustered (Kangas et al. 2004). Since forest biodiversity has been emphasized in forest policies and on the operational forest management level, a broad selection of inventory methods for CWD have been introduced and tested.

In general, objects which are more interesting than others may be included in the sample with a higher probability; this may be because better results are desired. Thus, different units in the population may be included in a sample with different probabilities (Thompson 2002). The use of auxiliary information in combination with a field inventory has been studied widely (e.g. Ringvall et al. 2007). The multi-source National Forest Inventory of Finland, for example, utilizes satellite images in producing large area information about forest characteristics (Tomppo 1991). Due to the development of remote sensing, more accurate and lower-cost information is available to be used as auxiliary information. One of the most promising remote-sensing technologies for increasing the accuracy and efficiency of large-scale forest inventories is airborne laser scanning (ALS) (Næsset 2002; Maltamo et al. 2006), which produces a three-dimensional illustration of the forest area. ALS-derived variables can be used in producing probability layers, which represent, for example, the likelihood of CWD existing in each grid cell of the layer. ALS can be utilized in guiding the field inventory to the more interesting areas, and thus the efficiency of field sampling methods may be improved.

In this study, the possibility of utilizing ALS as auxiliary information by implementing point proportional to size (PPS) sampling in the location of sample units in simple random sampling (SRS) and adaptive cluster sampling (ACS) was studied with the forests in commercial use in Central Finland. The efficiency of PPS and PPS+ACS was compared with SRS and ACS, where auxiliary data is not utilized. The aim of this article is to present an extensive comparison of different ALS-derived probability layers in guiding the inventory of CWD in one large area from the perspective of efficiency.

2. Material

2.1 Study area and data collection

The field work for this study was carried out in the summer of 2007. The study area is located in Sonkajärvi district in Central Finland and the forest area assessed is in active commercial forest management use. The age structure of the stands in the area is slightly biased towards younger age classes, but all classes are present in the area. As typical in Central Finland, the area consists of a mosaic of mineral soils, water bodies and both drained and undrained peat lands.

The field data was collected by measuring randomly located 100-meter-wide strips in a north-south direction. All dead trees with a base diameter greater than 10 centimeters were measured. The characteristics recorded for the standing dead trees were the diameter at breast height (dbh) and total height. For snapped trees, the measured variables were the dbh, the lengths of the standing and downed parts and the direction of the downed part. For downed dead trees, the falling direction, the total length and the dbh were measured. If the snags were shorter than 1.3 metres or the breast height could not be assessed, the diameter in the middle was measured instead of the dbh. All the observations were located with GPS (Global Positioning System) devices and the differential corrected using a base station located in the same municipality.

For the simulation study, all the strips measured were artificially gathered to make a uniform area. The compilation was formed by replacing the strips measured in spatially true order into a new coordinate system so that the directions of the strips remained in a north-south direction. The total compilation area was 286 hectares, the dimensions of the rectangle being 1.1km*2.60km. The mean CWD volume in the study area was 2.69m^3ha^{-1}, and the volumes ranged between 0m^3ha^{-1} and 69.2m^3ha^{-1}.

2.2 Laser data and data processing

The Georeferenced ALS point cloud data from Sonkajärvi were collected on 27th and 28th July

2006 using an Optech ALTM 3100 scanner operating at a mean altitude of 2500 m a.g.l (above ground level), which resulted in a nominal sampling density of about 0.5 measurements per m^2 when the pulse frequency of 50 kHz was used. The data were captured using a half-angle of 15°, resulting in a swath width of 1350 m.

Both the first and last pulse data were recorded and the last pulse data were employed to generate a digital terrain model (DTM) using the method explained in Axelsson (2000). Above ground heights, i.e. canopy heights, for the laser points were obtained by subtracting the DTM at the corresponding location. The height distribution of the first and last pulse canopy height hits was used to calculate grid-wise percentiles for 0, 1, 5, 10, 20, …, 90, 95, 99 and 100% heights (h_0, h_1, …, h_{100}) (see Næsset 2004), and cumulative proportional crown densities (p_0, p_1, …, p_{100}) were calculated for the respective quantiles. All metrics were calculated separately for both the first pulse data and the last pulse data. ALS-based variables were calculated with a vegetation limit of 0.5 meters.

3. Methods

3.1 Producing the probability layers

CWD measurements and ALS data were available from an independent study area in Juuka in Eastern Finland (Kotamaa 2007). The laser scanning equipment and measurements from this area were similar to those from the Sonkajärvi study area. Thus, the correlations between the ALS-derived height-, density- and intensity metrics and the CWD volumes were studied in the data available from Juuka. Using this data, we searched for the ALS-derived height metric which had the best correlation with the observed CWD volume. Respectively, we also searched for the density-, intensity- and deviation metrics which best correlated with the CWD volume.

Furthermore, two logistic CWD volume models were used in producing the probability layers. Two different independent modelling data were available from Juuka and Sonkajärvi region and were used in constructing the models. The logistic regression model can be expressed as follows (e.g., Hosmer and Lemeshow 1989; Dobson 1990):

$$\mathrm{logit}(\pi_j) = \beta_0 + \beta_1 x_{1j} + \ldots + \beta_i x_{ij} \tag{1}$$

$$\Leftrightarrow \pi_j = \frac{\exp(\beta_0 + \beta_1 x_{1j} + \ldots + \beta_i x_{ij} + \varepsilon)}{1 + \exp(\beta_0 + \beta_1 x_{1j} + \ldots + \beta_i x_{ij} + \varepsilon)}, \tag{2}$$

where π_j is the probability for observation y_j, β_0 the constant of the model and β_i the parameter to be estimated for independent variable $x_{i.}$ x_{ij} is the ith independent variable connecting to the observation y_j and ε the error term of the model, j = 1, 2, …, N. Equation 2 is intrinsically bounded within the interval [0, 1].

Since the unknown model parameters are non-linearly related to π_j, Maximum likelihood (ML) method is used to estimate the model parameters in logistic regression (Alenius et al. 2003). The models were fitted using glm-function with the R software (R Development… 2006). The method searches the parameter estimates which maximize the log-likelihood function l (Eqn. 3) i.e. it finds the most probable values of distribution parameters for a set of data.

$$l = \sum_{j=1}^{N} \left[y_j \log \pi_j + (1 - y_j) \log(1 - \pi_j) \right] \tag{3}$$

In constructing logistic regression models, the existence of CWD (volume limit 0 m^3ha^{-1}) was given a binary outcome, and it was predicted with the continuous explanatory variables derived from ALS data. The model parameters and independent variables in the models were investigated in order to find the best fitting model in the modelling data. The models predict the probability of CWD existing in each grid cell. In the logistic model from Juuka, the parameter estimates for the model constant and independent variable l_h_{90} were -3.2607 and 0.3434, respectively; while the parameter estimates for the model constant and l_h_{30} in the local model from Sonkajärvi were -0.9907 and 0.1443, respectively. In the logistic models, l_h_{90} and l_h_{30} denote the height at which the accumulation of last return laser hit heights in the vegetation is 90% and 30%, respectively. However, it is worth noting that if locally fitted logistic models are used in practice in producing probability layers, the collection of field data for CWD modelling requires a field inventory, and that data as such could be used for estimating the sampling statistics of CWD volume in the area.

In this study, the total study area of 1.1km*2.60km was divided into grid cells of 20m*20m. In total six different probability layers were constructed, four of which were produced by calculating the ALS-based variables for each grid cell, and two of which were produced using logistic models to predict the probability of CWD existing in each grid cell. Thus, either the value of ALS-derived variables as such or the value predicted with the logistic regression models determined the probability of each grid cell in the probability layer.

3.2 Sampling methods

The simulated sampling methods were simple random sampling (SRS) and adaptive cluster sampling (ACS). In these sampling methods, the simulated plots were squares – equalling the size and the location of the grid cells in the produced probability layers. The sample plots were placed in the study area by drawing grids randomly and with replacement. In SRS the estimator for the mean CWD volume (m^3ha^{-1}) was calculated as the mean of the inventoried plots

$$\hat{\bar{y}} = \frac{1}{n}\sum_{i=1}^{n} y_i \, , \tag{4}$$

where y_i is the CWD volume (m^3ha^{-1}) on plot i and n is the number of plots. The variance estimate was obtained from the variation between the sample plots (see e.g. Gregoire and Valentine 2008) as

$$\hat{\mathrm{var}}\left(\hat{\bar{y}}\right) = \frac{1}{n(n-1)}\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2 \, . \tag{5}$$

An estimator for the standard deviation of mean CWD volume is obtained by taking the square root of its variance.

In ACS a population is divided into N units and an initial sample of size n_1 is selected of these units. In ACS, simple random sampling without replacement was used to select an initial sample of the population, and whenever the amount of dead wood in a sampling unit exceeded the initially set limit, four neighbouring units of that unit were added to the sample (Thompson 1990). The volume limit of 30 m^3ha^{-1} was used in this study, since it has been noticed to be effective in Finnish commercial forests (Pesonen et al. 2008a). The estimates for the population mean and variance were calculated using Horvitz-Thompson (HT)-estimator (Thompson 1990). If the network containing unit j is A_j, and m_j denotes the number of units in A_j, the probability that the initial sample intersects A_j is

$$\alpha_j = 1 - \frac{\binom{N - m_j}{n_1}}{\binom{N}{n_1}}. \tag{6}$$

An unbiased HT estimator for the mean is

$$\hat{\mu}_{HT} = \frac{1}{N} \sum_{k=1}^{\kappa} \frac{y_k^*}{\alpha_k}, \tag{7}$$

where κ is the number of distinct networks intersected by the initial sample and y_k^* is the sum of the *y* values for the *k*th network. The inclusion probability α_k is the same for all units in network *k*. The joint inclusion probability of networks *j* and *k* i.e the probability that one unit belongs to networks *j* and *k* is given by

$$\alpha_{jk} = \begin{cases} 1 - \dfrac{\binom{N - m_j}{n_1} + \binom{N - m_k}{n_1} - \binom{N - m_j - m_k}{n_1}}{\binom{N}{n_1}} & \text{for } j \neq k, \text{ and} \\ \alpha_j & \text{otherwise.} \end{cases} \tag{8}$$

The unbiased estimator for the variance of $\hat{\mu}_{HT}$ is

$$\hat{\mathrm{var}}(\hat{\mu}_{HT}) = \frac{1}{N^2} \left[\sum_{j=1}^{\kappa} \sum_{k=1}^{\kappa} \frac{y_j^* y_k^*}{\alpha_{jk}} \left(\frac{\alpha_{jk}}{\alpha_j \alpha_k} - 1 \right) \right]. \tag{9}$$

In the selection of sampling units, it is possible to select the units by utilizing some previously available information and taking into account that each unit in the study area may not have the same inclusion probability. In this study, the plots were placed in the study area by utilizing ALS data as auxiliary information. The probabilities of CWD existing were derived from the produced probability layers, and the sample plots were placed in the grid cells with a probability proportional to the predicted probabilities.

In unequal probability sampling with replacement, PPS, an unbiased estimator for the population total is obtained as (see e.g. Thompson 2002)

$$\hat{\tau}_p = \frac{1}{n} \sum_{i=1}^{n} \frac{y_i}{p_i}, \tag{10}$$

where p_i is the probability of selecting the *i*th unit of the population, for *i* = 1 , 2, …, *N*. In this study, the total CWD volume estimated from plot *i* was calculated by summing the observed volumes in a grid cell *i* and dividing the sum with the ALS-based estimate for the probability of a grid cell *i* to be included in the sample. The estimate for the mean volume per hectare was calculated by dividing the estimated total volume with the study area in hectares.

Similarly, in ACS it is possible to select initial sampling units with unequal probabilities. Roesch (1993) and Smith et al. (1995) have used PPS sampling in ACS in inventorying rare and clustered characteristics of trees and the number of wintering waterfowls, respectively. Smith et al. (1995) have presented the calculation of the estimates with unequal probabilities in ACS (PPS+ACS). In PPS+ACS the Equations 7 and 9 were used in calculating the estimators for the mean and variance. However, the intersection probabilities were then calculated as

$$\alpha_j = 1 - \left(1 - \frac{a_j}{A^*}\right)^{n_1} \quad \text{and} \tag{11}$$

$$\alpha_{jk} = \begin{cases} \alpha_j + \alpha_k - \left[1 - \left(1 - \dfrac{a_j + a_k}{A^*}\right)^{n_1}\right] & \text{for } j \neq k \text{, and} \\ \alpha_j & \text{otherwise.} \end{cases} \tag{12}$$

In Equations 11 and 12 a_j denotes the probability of CWD existing in the *j*th network and A^* is the sum of predicted probabilities in the study region.

3.3 The simulation and comparison of different sampling methods

The alternative sampling methods with different probability layers were simulated in the study area where every downed and standing dead wood log was precisely located. The simulations were made for the combined CWD volume including both CWD materials.

Once the sample units were placed in the study area, the accuracy statistics for the simulated sampling methods were calculated based on the field measured CWD data. The estimates for the population mean, absolute and proportional standard error of mean were calculated. Different sampling methods were simulated with the study area 500 times. The mean and variance estimators in each simulation were calculated with equations specific to each sampling method, and the average of these was the mean and variance obtained for the specific sampling method.

Since the costs of field inventory methods vary depending on the measurement time and the travelling time between the plots, the time consumption of each sampling simulation was taken into consideration. For each sampling approach, the achieved accuracies with a fixed inventory time were calculated in order to make the different sampling strategies comparable.

4. Results

Different ALS-based probability layers were utilized in the placement of the sample units in PPS and PPS+ACS and the accuracy of the layers were compared in terms of the precision of the estimated mean CWD volume in the area by additionally taking into account the required inventory time of each sampling approach. The precision of the estimates varied notably between different probability layers.

The probability layers were formed using the variables which were observed to have the highest correlation with CWD volume. Thus, correlations were only analyzed in order to find the variables which have the highest correlation with CWD volume and the correlations were not utilized as such in producing the probability layers, but the layers were formed by calculating the value of the ALS-based variables for each grid cell of the layer. The ALS-derived height-, density-, deviation-, and intensity metrics which had the highest correlation with CWD volume in the Juuka data and the respective strengths of the correlations and their directions in the Sonkajärvi data are shown in Table 1. The correlations were similar in both regions. The ALS-derived heights at the upper percentiles captured by the first pulse and the standard deviation of heights had the strongest correlation with CWD volume. If the standard deviation of laser pulse heights increased, greater CWD volumes were observed in both areas, for example.

Table 1: The strengths and the directions of the correlations between CWD volume (m^3ha^{-1}) and ALS-based variables.

ALS-based variable[a]	Juuka	Sonkajärvi
f_h_{60}	0.366	0.320
f_h_{std}	0.327	0.301
l_i_{10}	-0.183	-0.151
f_p_{90}	-0.141	-0.103

[a] The prefix *f* or *l* denotes the laser pulse type, first or last pulse, h_{60} denotes the height at which the accumulation of laser hit heights in the vegetation is 60%, h_{std} is the standard deviation of the height distribution pulses. The p_{90} denotes the proportion of laser hits accumulating at the 90% height and i_{10} is the value of intensities accumulated in the 10th percentile.

The higher the correlation between CWD volume and the ALS-based variable was, the more improvement in the accuracy of volume estimates was usually achieved while utilizing probability layers in guiding the placement of sample plots. With a given inventory time in SRS, utilizing probability layers produced from ALS metrics of f_p_{90}, l_i_{10}, f_h_{60} and f_h_{std} produced 4%, 6%, 13% and 15% smaller standard errors of the mean for the CWD volume estimate, respectively (Figure 1); the respective improvements in the accuracy of ACS were 3%, 5%, 9% and 11% (Figure 2). The utilization of probability layers produced using logistic models applied in the Juuka and Sonkajärvi regions improved the accuracy of SRS with 8% and 10%, respectively, while the accuracy of ACS improved with 6% and 7%. Thus, the locally fitted logistic model was more accurate, but the ALS-derived height- and deviation metrics improved the accuracy of the estimates even more.

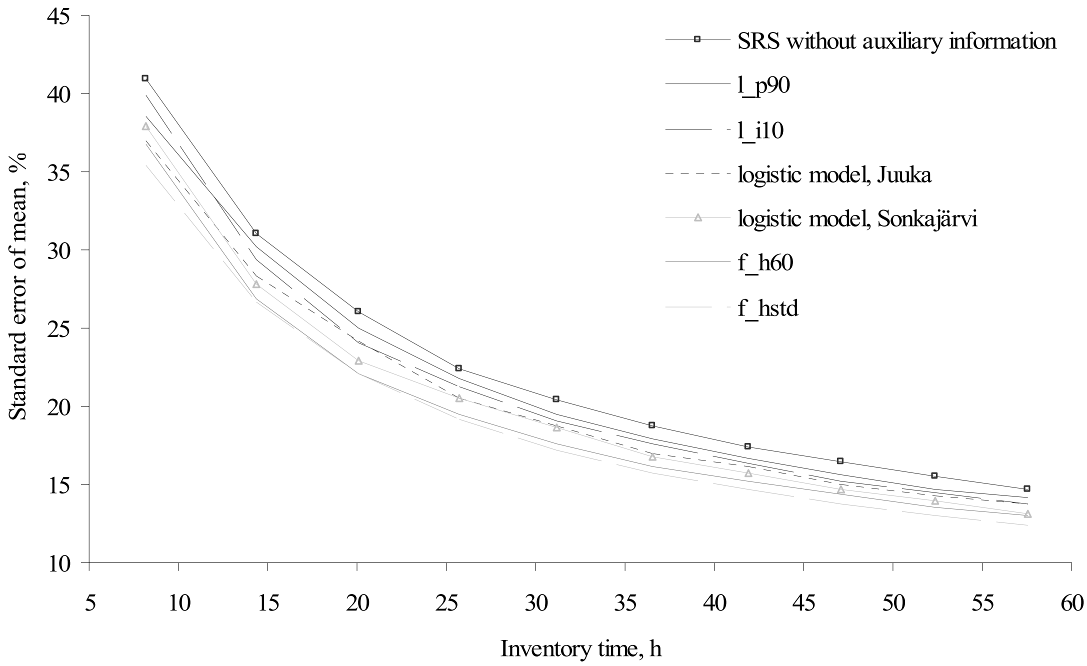

Figure 1: The standard error of mean for the CWD volume estimates in SRS without auxiliary information and utilizing different ALS-based probability layers.

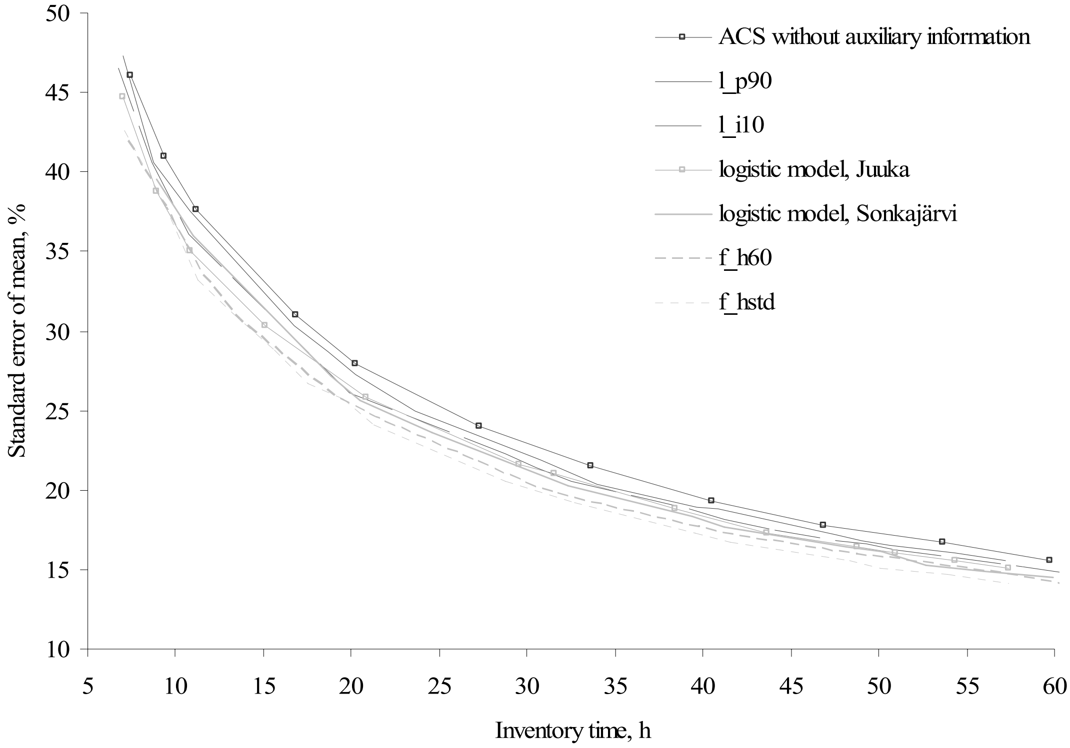

Figure 2: The standard error of mean for the CWD volume estimates in ACS without auxiliary information and utilizing different ALS-based probability layers.

5. Discussion

Since CWD is recognized to be a key factor for biodiversity in boreal forests, recently inventory techniques for assessing CWD have been developed (e.g. Thompson 1990; Buckland et al. 1993; Ståhl 1997). However, field surveys can still be expensive. This study focused on the possibilities for improving the efficiency of field inventories with SRS or ACS by utilizing different ALS-based probability layers as auxiliary information.

The utilization of probability layers in the guidance of field inventories improved the accuracy of CWD volume estimates. The efficiency of SRS and ACS could be improved notably when utilizing probability layers produced from ALS-derived height metric and standard deviation of heights, but only slight improvements were achieved when the probability layer was constructed from ALS-derived density- or intensity metrics, since there was only minor correlation between CWD volume and these variables. The efficiency of probability layers derived from both a locally fitted logistic CWD model and a logistic model from a separate area was weaker than direct ALS-derived height metrics, since the correlations between CWD volume and the predictions of logistic models were weaker. It could also be possible to combine different ALS variables in probability layers. Coefficients for these variables could be searched for by means of optimization or by modelling. However, in the case of modelling the drawback would be statistically non-significant independent variables in the constructed models.

Even the utilization of a locally fitted logistic CWD model could not improve the accuracy of SRS and ACS as much as direct ALS-derived variables. The same result was obtained when utilizing two linear regression models which were constructed using data available from Juuka and Sonkajärvi. Furthermore, there were considerable difficulties in the construction of linear regression models for predicting CWD volumes. The observed high accuracy of ALS-based probability layers compared to model-based layers improves the usability of direct ALS metrics since then any previously fitted model and expensive modelling data for predicting the probabilities in grid cells are not required. Therefore, the usability of ALS-derived probability layers in guiding the field inventory is relevant and prior information about the correlations between the existence of CWD and ALS-based variables can be used in constructing the probability layers. This information can be obtained from nearby areas which have older modelling data, such as from Juuka in our case. Like Pesonen et al. (2008a, 2008b), this study found that CWD volume is strongly correlated with ALS-derived heights and the standard deviation of height pulses. Hence, these variables can be used in constructing the probability layers and used in making the field inventory more efficient; or, respectively, for achieving a given accuracy level less inventory load is needed.

This study focused on estimating the combined CWD volume including both downed and standing dead trees. The probability layers can also be produced separately for different CWD materials if the combined CWD volume is not in focus. It was observed in this study that the standard deviation of heights captured by the first pulse ALS data and the heights at upper percentiles correlated strongly with both downed and standing dead wood volumes. The utilization of probability layers which were constructed separately for both CWD materials, improved the accuracy of volume estimates in a manner similar to the case of combined CWD volume.

The direct estimation of CWD volumes in commercial forests have proved to be challenging with sparse pulse ALS data and only the accuracy of logistic regression with a volume limit of $0 m^3 ha^{-1}$ has proved to be appropriate (Kotamaa 2007); however, ALS data is suitable as auxiliary information in making the field inventory more efficient. The utilization of probability layers in guiding the field inventory of CWD is a new approach and while the costs of ALS data are decreasing quickly, data from increasingly large areas is being acquired. In this study, the costs of ALS data were assumed to be zero, which naturally is not true. Nowadays, while the inventory of living trees could be done accurately enough by utilizing ALS (e.g., Næsset 2007), the same ALS data, which is originally gathered for other purposes, could be utilized in CWD inventories as well. Further studies are focusing on how auxiliary information derived from ALS data could also be utilized in other field inventory methods than SRS and ACS.

Acknowledgements

The authors thank Ms Eveliina Kotamaa for her assistance in calculating the CWD volumes for the Juuka region and Dr Lauri Mehtätalo for his comments on the text. Many thanks are also due to the SilviLaser 2008 team for putting this format template together. This study is a part of the project "Mapping rare forest characteristics using remote sensing material and field data (decision No. 116313)", funded by the Academy of Finland.

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