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Updating of forest stand data by using recent digital photogrammetry in combination with older airborne laser scanning data

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ABSTRACT
Accurate and up-to-date data about growing stock volume are essential for forest management planning. Airborne Laser Scanning (ALS) is known for producing accurate wall-to-wall predictions but the data are at present collected at long time intervals. Digital Photogrammetry (DP) is cheaper and often more frequently available but known to be less accurate. This study investigates the potential of using contemporary DP data together with older ALS data and compares this with the case when only old ALS data are trained with recent field data. Combining ALS data from 2010 to 2011 with DP data from 2015, both trained with National Forest Inventory (NFI) field plot data from 2015, improved predictions of growing stock volume. Validation using data from 100 stands inventoried in 2015 gave an RMSE of 24.3% utilizing both old ALS data and recent DP data, 26.0% for old ALS only and 24.9% for recent DP only. If information about management actions were assumed available, combining old ALS and recent DP gave RMSE of 23.0%, only ALS 23.3% and only DP 23.8%.

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Forest inventory; forest growing stock volume; airborne laser scanning; digital photogrammetry; thinning; updating forest data

Introduction

Up-to-date and accurate data about the forests is important for forest management planning. Airborne laser scanning (ALS) has revolutionized forest inventory, providing accurate and high-resolution data. ALS-based methods, such as the area-based method where predictions are made for raster cells (Naesset 2002), can for large areas provide cost-efficient predictions of key forest variables with an accuracy that in many cases is sufficient for forest management planning (Næsset et al. 2004; Nilsson et al. 2017). Forestry has long relied on forecasting functions to keep forest data updated (Wikström et al. 2011). Variations in growth, damages and natural mortality, will however gradually reduce the accuracy of such forecasted data. Management actions will also change the state of the forest. Thinning, where typically about 30% of the basal area is removed, is carried out as a standard procedure in Swedish forestry. Annually around 2% of the productive forest land is thinned and 1% is finally felled in central Sweden. Average annual growth rates of growing stock volume are in the range of 7–8 m^3/ha in the same area (Nilsson et al. 2015). Even if an ALS-based prediction is accurate at the starting point, an update is thus necessary after a few years. Incorporating more frequently available data sources, possibly in combination with the older ALS data could be one option to create such an update.

Three-dimensional (3D) point clouds, similar to the ones produced from ALS, can also be obtained from Digital Photogrammetry (DP). In the case of Sweden, the current second national laser scanning program will take at least seven years, whereas aerial photos with stereo overlap on average are acquired by a government program every third year (Lantmäteriet 2019). From the air photos, a 3D point cloud can be obtained by image matching of the overlapping stereo images (Ginzler and Hobi 2015). This DP point cloud will mainly provide data about the height of the forest canopy that can be used in an area-based approach, for predictions of forest variables together with a Digital Elevation Model (DEM) from ALS (Bohlin et al. 2012).

The Swedish National Land Survey (Lantmäteriet) has since the year 2009 been scanning Sweden with ALS, originally to produce a nationwide DEM with 2 × 2 m grid cells (Lantmäteriet 2019). The ALS data have also been used to produce maps of forest attributes (typically Lorey's mean height, basal area, volume, mean diameter) in raster format by several forest companies as well as by the Swedish University of Agricultural Sciences (SLU) in cooperation with the Swedish Forest Agency (Nilsson et al. 2017). A new second national laser scanning of Sweden, primarily for the needs of the forest sector and co-financed between the government and the forest sector, started during 2018.

A markedly different property of DP compared to ALS is that the former mainly relates to the upper part of the canopy. Several studies have found that stand density-related measures and lower canopy information are less accurate from DP than from ALS (St-Onge et al. 2008; Bohlin et al. 2012; Vastaranta et al. 2013; Gobakken et al. 2015). The better results with ALS in particular for variables that are related to stand density are confirmed in studies where predictions from ALS are directly compared with predictions from DP

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using the same test area and reference data (Rahlf et al. 2014; Yu et al. 2015; Hawryło et al. 2017; Ullah et al. 2017). The results by Bohlin et al. (2017) showed that predictions of volume (and other forest variables) from ALS data that were 3–6 years older than the DP data still were slightly better than volume predictions using the more recent DP data. That study discarded, however, any plots that had been subject to management actions since the ALS data acquisition.

Focusing on the forest where no harvest has occurred, several recent studies have used the framework of data assimilation to combine new and old data using forecast models to update earlier predictions (Ehlers et al. 2013; Nyström et al. 2015; Lindgren et al. 2017; Ehlers et al. 2018). These early data assimilation studies used the extended Kalman filter (Kalman and Bucy 1961). When using the Kalman filter, the forest data is forecasted and iteratively combined with new remote sensing data with weights being based on the prediction errors for the different data sources. Only the combined prediction together with its error estimate needs to be carried on to be combined with the next data set at a later time point. Empirical results from the above-cited studies about data assimilation show that the methods need to be developed further before their potential can be realized. Goodbody et al. (2017) investigated a method to update predictions after selective harvest using drones. By combining metrics from ALS and very high-resolution DP from drone imagery, an updated map was created. The study by Goodbody focuses on the selectively harvested sites only. However, changes such as growth and damages also affect the state of the forest. Potentially, information related to these changes could be found in the difference between two datasets in a time series.

Whereas site index and age are needed in the forecasting step of data assimilation, these data are often not available for large-area mapping. A straightforward way to obtain updated predictions from old ALS data might instead be to use the ALS data for direct modeling with the aid of up-to-date field reference plots. The old ALS data carries information about the stand structure that also could be combined with the more recent data from DP. One way to achieve this is by using metrics from both older ALS data and recent DP data in one model developed using present field reference plots. Furthermore, changes that have occurred after the ALS data acquisition and are difficult to detect with DP, such as thinning (Ali-Sisto and Packalen 2017), should be considered when they are known. The forest owners usually have information about their past management activities, but such register data is usually not available for government organizations making wall-to-wall forest resource maps for large areas.

One aim of this article is to investigate if the prediction accuracy of present stand level growing stock volume can be improved by combining old ALS and present DP data in the same predictive model. The model using the combined datasets is compared to models using each dataset separately. In contrast to the similar study by Bohlin et al. (2017), we also aim to examine how stands that were thinned since the ALS acquisition affect the result, both when these management actions are assumed to be known and when that information is unavailable. Our results show that predictions based on old ALS and recent DP in combination only were marginally better in terms than using either old ALS or recent photogrammetry alone given that abrupt changes like thinning cuttings are known.

Materials and methods

Study area

The study area covers about 120 by 120 km in eastern Sweden (Figure 1). Norway spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*) in pure or mixed stands dominate the forest in the area. There is also a smaller proportion of deciduous tree species, mainly birch (*Betula spp*). Forest management in the area usually includes the planting of conifers, pre-commercial thinning followed by one or several thinnings for commercial purposes and final felling.

Sample plots from the Swedish National Forest Inventory

The Swedish National Forest Inventory (NFI) (Fridman et al. 2014) regularly assess the forest over the entire country using two sets of objectively selected sample plots: one permanent set where plots are measured every five years, and one temporary set that is not revisited. Permanent sample plots have a radius of 10 m and temporary 7 m. Sample plots are located along the perimeter of rectangular clusters. The NFI positions the plots using standard handheld GPS-units, but some of the plots have also been positioned using precision GPS devices, see Nilsson et al. (2017) for information about the positioning of the NFI plots. On each plot, tree stems are measured on concentric plots with different

Figure 1. Geographical location of the study area in eastern Sweden.

sizes depending on the diameter at breast height (dbh) of the trees. For trees on temporary and permanent plots with a dbh > 100 mm, stem diameters are measured on circular plots with 7 or 10 m radius, respectively. Smaller trees with a dbh > 40 mm and trees with a dbh > 0 mm are measured on plots with 3.5 or 1.0 m radius, respectively, on both temporary and permanent plots. For a subsample of the trees, the height is measured as well. In addition, any forestry activity such as thinning or final felling is recorded and the time since the action is assessed. Site index is evaluated according to site properties (Hägglund and Lundmark 1977), which together with age and the forest state at the time for inventory was used for prediction of Current Annual Increment of volume (CAI) (Wikström et al. 2011). The temporary and permanent plots measured in 2014 and 2015 from the NFI made up the forest reference dataset for this study. Ten percent of the plots which had been subject to final felling after the ALS data acquisition were removed. A few plots were found to have obvious coordinate errors and one plot had been finally felled since the field inventory date. These outliers were also removed from the data, leaving 262 plots for the final development of the models. To represent the forest state in 2015, one year of CAI was added to plots that had been measured in 2014.

Validation stands

The results were evaluated using 74 stands objectively inventoried by forest companies in the study area. These stands were measured for forest holding inventories in 2015 following the procedure of the Forest Management Planning Package (Jonsson et al. 1993). Out of these, 22 stands were randomly sampled from stands that had not been thinned before. In addition to these, 26 stands that had been thinned since the ALS acquisition were selected and measured. The validation stands were between 0.4 and 49.5 ha (mean 9.8 ha) and were measured using a systematic sample of 3–12 plots per stand (depending on the size of the stand) with 8 m radius placed in a regular grid. Diameters at breast height were measured for all trees on the plots above 5 cm using a caliper. Height and age (via core drilling) were determined for a subsample of the trees (on average 1.5 trees per plot). Forest attributes at stand level were derived by averaging plot level attributes. Statistics about the sample plots used for model development and validation stand data is given in Table 1.

Remote sensing data and predictor variables

The ALS data from the Swedish National Land Survey were acquired in scan blocks of nominally 25 × 50 km, planned to be scanned in one day. In the study area, there were 11 blocks of ALS acquisitions. Two different types of scanners were used: Leica ALS 60 and Optech ALTM Gemeni. The blocks were scanned during 2010–2011 and during different seasons (Table 2). The scannings were performed from flying heights between 1700m and 2300 m resulting in a point density of 0.5–1 pulses/m2 and a 20% side-lap between scanning strips. The maximum scan angle was 20°.

Table 1. Descriptive statistics of the field inventory data sets. Models for the volume per hectare (ha) were developed using NFI plots and evaluated on the validation stands data sets. The number of observations refers to sample plots for the NFI plots, while for the validation stands it refers to the number of stands measured.

Field data set	Number of observations	Proportion thinned	Median volume	Volume IQ range
Validation stands	100 stands	33%	167 m^3/ha	114 m^3/ha
NFI plots	262 plots	10%	190 m^3/ha	156 m^3/ha

Based on the date in combination with historical weather data and phenology observations, the season of the acquisitions was subjectively classified as leaf-off or leaf-on (Nilsson et al. 2017).

The Swedish National Land Survey repeatedly acquires aerial images with stereo overlap covering the whole country. Images over the study area were acquired in 2015 during leaf-on season. The flight height was 3700 meters above ground level. The camera was a Vexel UltraCam Eagle triggered for a 60/30% overlap (along flight line/cross flight lines) and the pixel size was 25 cm (Lantmäteriet 2019). Digital stereo matching to point clouds was done using the state of the art software SURE from nFrames (Rothermel and Wenzel 2012; Wenzel et al. 2013) which uses the semi-global matching method (Hirschmuller 2008). Settings for aerial images with 60/30% overlap were applied.

Processing of both point clouds from DP and ALS followed a standard area-based approach (Næsset et al. 2004). First, the two datasets were normalized to the height above ground, using the DEM produced by the Swedish National Land Survey from the same ALS data as used in this study. Normalized points with a height above 50 m or below −2 m were discarded. Only first or single returns in the ALS point cloud were retained in order to minimize the influence of different data acquisitions (Bater et al. 2011). In addition, where points from adjacent flight lines overlapped, only the points with the lowest scan angle were kept. Points within the sample plots were extracted and area-based metrics were calculated using FUSION (McGaughey 2014). The metrics included height percentiles (P), the square root of quadratic average (QuadMean) and the third root of the cubic average (CubeMean) of the points' heights above ground. Metrics also included vegetation ratios calculated as the proportion of points above a height threshold ($VR_{Threshold}$). Thresholds used were 2 m (Nilsson 1996), the mean and median of the points. The same set of metrics were also calculated for raster cells with size 12.5 by 12.5 m covering the entire study area. For more details on all metrics calculated refer to the FUSION manual (McGaughey 2014).

Table 2. Number of NFI sample plots per property of the ALS acquisitions: Season for leaf-off or on conditions and scanner manufacturer. The values represent the number of plots per combination of the two properties, and the sum is the total number of plots per property.

Scanner/season	Leaf-off	Leaf-on	Sum:
Optech	80	52	132
Leica	60	70	130
Sum	140	122	

Model development

Ordinary Least Squares regression was used to develop models for prediction of growing stock volume corresponding to the forest state of 2015. The NFI sample plots were used as reference data for the model development. Three different sets of predictor variables were examined:

(i) Only DP metrics.
(ii) Only ALS metrics.
(iii) All available metrics, both the old ALS data and the present DP metrics in one model.

In addition, each set of predictors were tested in combination with an indicator variable if the plot had been thinned in the time between the ALS acquisition and the field measurement of each plot. This thinning variable (denoted IND) was based on the NFI data of management history assessed on the plots during the field measurement. Plots that were subject to final felling in the time between the laser data and the aerial image acquisition were excluded from the analysis.

A linear regression model predicting growing stock volume was selected for each set of predictor variables using forward selection. Two transformations of the dependent variable were evaluated: square root transformation and natural-logarithm transformation. Square root transformation was selected after studying residual plots, and MSE of the back transformed residuals. Regression diagnostics (*p*-values and Akaike information criterion) were used for the selection of metrics and the appropriate number of predictor variables to retain in each model. IND was tested for effect on either intercept, slopes of other variables or both. The preliminary models were fitted, and large outliers were examined with an ortho-photo as a background. We examined differences in ALS acquisition properties using indicator variables added to the intercept and/or the slope of the models. Indicators were scan area, scanner manufacturer, year of acquisition and leaf-off or leaf-on conditions. To test if there was a detectable effect of the growth between the ALS acquisition and the prediction time point, the predicted CAI by Heureka on the sample plots was tested for significance. This was done to discern any trends in the data due to the old ALS data, trained with new sample plots material.

A correction factor (f) for back transformation bias was calculated (Snowdon 1991) as the ratio of the untransformed reference values (y_i) over the back transformed uncorrected fitted values $\hat{y}_{i,\,sqrt}$:

$$f = \frac{\sum_i^n y_i}{\sum_i^n \hat{y}_{i,\,back-transformed}}.$$

All models were then used to predict volume in grid cells of the metrics rasters. Predictions were back transformed and the correction factor f was applied. Predicted growing stock volume for each validation stand was then calculated as the average of raster cells with their cell center within the stands in the validation data set. Deviations ($d_i = y_i - \hat{y}_i$) were calculated from the field measured growing stock volume of the stand. Accuracy of the predictions was assessed by RMSE, bias and their relative measures to the mean growing stock volume of the validation stands ($\bar{y}$):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(d_i)^2},$$

$$rRMSE(\%) = 100 \times \frac{RMSE}{\bar{y}},$$

$$Bias = \frac{1}{n}\sum_{i=1}^{n}(d_i),$$

$$rBias(\%) = 100 \times \frac{Bias}{\bar{y}}.$$

Results

Model development with NFI plots

Power-weighted mean height metrics (CubeMean, QuadMean) showed to be strong predictors for both DP and ALS models. All models including ALS data performed best in terms of R^2-adjusted if QuadMean was selected, while for DP CubeMean was preferred. For ALS, we found different VR metrics to be the second most important and a small improvement was also obtained when we added a low percentile (P01-P30). For DP models, a low percentile was more important than any VR metric, but VR_{2m} was still improving the model. Selected metrics for different models are presented in Table 3. Models that combined ALS and DP metrics contained similar metrics that were found to be important when modeling the sensors separately. QuadMean from ALS along with the DP metrics VR and MinH gave more precise models than other candidate models using metrics with higher correlation with H_L from DP, and VR metrics from ALS.

The indicator variable IND showed a greater effect for ALS only models. This variable indicates if the stand or sample plot was thinned in the time since the ALS data acquisition. There was a significant effect when IND was included in the DP only model, and also for the combined ALS/DP models. Indicators (season, scanner) to test for the effect of different properties of ALS acquisitions (Table 2) showed no significance for any model and was left out from the models. Residual studies showed that growth (CAI) made no significant contribution to any of the models, including the ALS only and ALS + IND models where the ALS data were acquired some 4–5 growing seasons prior to the field data. All models showed a trend for the residuals over deciduous proportion, measured as the proportion of the growing stock volume,

Table 3. Selected model forms for different combinations of sensor data (ALS and DP) as well as the indicator variable for thinning (IND).

Sensor data	Selected metrics	R^2
ALS + DP + IND	IND, $QuadMean_{ALS}$, $MinH_{DP}$, $VR_{DP,2m}$	0.849
ALS + DP	$QuadMean_{ALS}$, $MinH_{DP}$, $VR_{DP,2m}$	0.847
DP + IND	IND, $CubeMean_{DP}$, $MinH_{DP}$, $VR_{DP,2m}$	0.821
DP	$CubeMean_{DP}$, $MinH_{DP}$, $VR_{DP,2m}$	0.821
ALS + IND	IND, $QuadMean_{ALS}$, $P10_{ALS}$, $VR_{ALS,mean}$	0.834
ALS	$QuadMean_{ALS}$, $P10_{ALS}$, $VR_{ALS,mean}$	0.825

Table 4. Validation results for model predictions of volume at 100 stands. Different sets of sensor data (ALS and DB) as well as an indicator variable for thinning (IND) were used when developing models with NFI plots as reference data.

Metric group	rRMSE (%)	rBias (%)	rBias, thinned (%)	rBias, un-thinned (%)
ALS + DP + IND	23.0	−1.1	−5.7	0.54
ALS + IND	23.3	1.5	0.15	1.8
DP + IND	23.8	−6.2	−15.2	−3.0
ALS + DP	24.3	−3.6	−17.3	1.4
DP	24.9	−7.7	−21.9	−2.5
ALS	26.0	−2.9	−22.6	4.2

and all models were also significantly improved by adding deciduous proportion, measured at the NFI plots, as a variable in the models.

Validation at stand level

We present results for model predictions of the validation stands in Table 4, with models ordered from lowest to highest RMSE.

All models including IND performed better than models without IND. Among the models including IND, differences in RMSE were lower, with the two models ALS + IND and ALS + DP + IND performing best. The ALS + DP model showed lower RMSE compared to only ALS. Comparing ALS + DP to the DP model the rRMSE was only 0.6% units lower for the combined model.

We found that the biases for thinned stands were large for many models, while it was reasonably low for the un-thinned stands. The negative bias means a prediction on average being higher than the true reference value. Recent DP data showed bias for thinned stands in the same range as for the model based on only old ALS data. DP + IND model showed almost as large bias, despite the inclusion of the IND variable, indicating if the forest was thinned or un-thinned since the timing of the ALS scanning.

Discussion

Model development with NFI plots

The main goal of this study was to identify and compare approaches to update forest stand information and look at the sources of errors with a special interest in volume change and management actions on primarily old data. We analyze how to make use of new 3D-data from DP given that older laser data exist: Discard old data and only use the new data or combine them to get the best updated stand register data. Given the current situation, where DP is more frequently available compared to ALS, effects on combining the data are relevant for operational forestry. If DP can give information about changes and growth during the time since an ALS scanning.

The issue of updating forest variable predictions by combinations of datasets has been addressed in other studies as well (e.g. Pippuri et al. 2013). A modeling approach to update growing stock volume after selective harvest was suggested by Goodbody et al. (2017). In that study, DP point clouds from drones were used in combination with pre-harvest ALS data with promising results. Data assimilation is another approach to combine predictions (Ehlers et al. 2013; Nyström et al. 2015; Lindgren et al. 2017; Ehlers et al. 2018). In the data assimilation approach, using for example an extended Kalman filter (Kalman 1960; Kalman and Bucy 1961), the combination of different data sets is split into two parts: (1) update old data through forecast models, (2) combination of forecasted data with new data through weighting inversely proportional to their respective uncertainties. Input data required for the growth forecast models are normally not available in large-area applications. In addition, changes would have to be addressed in the data assimilation approach as well since they would affect the updates.

Not surprisingly, the IND variable was important for models using the old ALS data. Based on what has been noted in previous studies (e.g. Bohlin et al. 2017), it was also expected that incorporating DP data would not solve the issue of over-estimating thinned stands. A major drawback of DP data for forest applications is its recognized lack of density-sensitive information. Therefore, it was expected that a model with density-related metrics from ALS and height-related metrics from DP would perform well. Surprisingly, the model with QuadMean from ALS combined with VR and MinH from DP performed best, better than models with VR from ALS. Our interpretation is that QuadMean is height related but also density related, and therefore a suitable metric from ALS.

Estimating a function that combines different data sources demands a sufficient number of reference data with a complete set of independent variables for each sample plot. Each ALS block of 25 × 50 km is too small for obtaining enough NFI plots. Thus blocks scanned during different dates and with different scanners had to be used in the same prediction model. Visual inspection of the predicted raster could in this study not reveal the different scan areas scanned with different scanners, nor did any dummy variable tested and therefore the models were fitted to the whole area. Season has previously been regarded as an important factor (Nilsson et al. 2017), and the lack of significance might be related to the scarcity of deciduous-dominated plots in this particular rather than the lack of an effect. The result that predicted CAI from Heureka on the sample plots was not significant to the model, was probably because the time since the ALS scanning is relatively short and other error sources are more important.

Validation at stand level

The obtained results for DP are similar to previous studies where large areas have been predicted and evaluated at stand level (Bohlin et al. 2017). Some other studies (Gobakken et al. 2015; Yu et al. 2015) have obtained better results for DP. A reason for this might be that our study was carried out within a large area with varying forest conditions.

The results show that the combination of old laser data and recent photogrammetry data, trained with recent field data, provided the best predictions both when thinning cuttings were known and unknown. In the case when thinnings were unknown, the improvement when combining DP and ALS in terms of RMSE was only minor compared to DP only. ALS without the IND, the indicator variable for thinning, had considerably higher RMSE. The validation dataset has a high proportion of thinned stands compared to what is expected in a random sample such as the NFI training data. This will affect the result, in particular for the old ALS data, but also for DP data that is less sensitive to the stand density. The bias for the thinned stands is severe for all models not including IND. This confirms the lack of density-related information in DP data.

The knowledge of thinning cuttings improved results for all models. In particular, the use of old ALS data in combination with IND performed better than using only recent DP data or DP data including IND. The RMSE of models utilizing ALS and knowledge about thinning were only 0.3% units higher than models also including DP metrics. The DP + IND bias in thinned stands was surprisingly large, despite the IND variable being included in the model.

The results highlight that, if old laser scanning data are available, incorporating new data from a less information-rich source such as point clouds from photogrammetry is less valuable when changes are known. The case where management actions are not known, but older information in general is of high quality, contrasts this. In this case, more up-to-date information should be considered. This article shows that combining ALS and DP, or just using DP data, is valuable in keeping stand data up to date. It is expected from previous studies that ALS show good results compared to DP. The advantage of the frequent availability of DP does not fully out-compete the advantage of the better information content of the ALS in this study, especially when management actions are known. Thus, using even a few years older ALS together with recent field data and knowledge about thinning appears to be a practical solution for keeping stand registers up to date, and an alternative to using forecasting functions. It should however be kept in mind that this method does not compensate for differences in site index and can thus only be recommended for a few years of forecasting. In this study, growth (CAI) since the time of the ALS acquisition did not show any significant trend in any model. This study was done over a relatively short period of time, and longer intervals would probably increase the importance of CAI and therefore possibly the value of including DP into an old ALS prediction.

Conclusion

We found a small improvement by combining older ALS with recent DP data sets, both when thinning since the acquisition of the ALS data was assumed known and assumed unknown. The quality of ALS data could be maintained if thinnings were included in the model, yielding better result than DP data and almost as low RMSE as the combination of ALS and DP. In case thinnings were not known, DP data had lower RMSE than ALS. An even lower RMSE was found for the combination of DP and ALS in this case, but the improvement was only minor. These results also highlight the importance of detecting changes to the forest for maintaining the accuracy of forest predictions.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The sample plot reference data from the Swedish National Forest Inventory contains confidential information and will not be shared. Due to ownership of the data by private forest companies, the stand evaluation data will not be shared. The aerial images and the airborne laser data used in this study can be acquired from the Swedish National Land Survey (Lantmäteriet).

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