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Abstract

Customer-oriented production as a sawmill strategy requires up-to-date information on the available raw material resources. Bucking is a process where the tree stem is divided into products based on the roundwood user's needs regarding products and their quality and dimensions. Optimization methods are employed in bucking to recover the highest value of the stem for a given product price matrix and requested length-diameter distribution. A method is presented here for assessing the value of harvestable timber stands based on their product yield. Airborne laser scanning, multispectral imagery and field plots were used to produce timber statistics for a grid covering the target area. The statistics for the plots were generated from this grid. The value of the estimated tree list was assessed using a bucking-to-value simulator together with a stem quality database. Different product yield simulations in terms of volumes, timber assortment recoveries, wood paying capabilities (WPC) and value estimations based on the presented method and extensive field measurements were compared. As a conclusion, this method can estimate WPC for pulpwood and sawlogs with root mean squared errors of 32.7 and 38.5 per cent, respectively, relative to extensive field measurements.

Keywords

Timber stand valuation; bucking; diameter distribution; product yield pricing; timber assortment recovery.

Introduction

Many Nordic sawmills employ a customer-oriented strategy in their production, which means that customer orders determine the length, small-end diameter and quality distributions of logs delivered to a sawmill (Helstad 2006). Thus assessments of harvesting output must be based not only on single volumetric figures, but also on comparisons between the demand and actual output length-diameter distributions of logs (Kivinen et al. 2005).

Timber buyers have to make pricing choices when purchasing roundwood at a given stumpage price, those who can buy stands that best fit their industrial process will benefit, since in competitive markets side products have to be sold at or below cost price.

Approximately 86% of Finland's commercial roundwood is removed in stumpage sale fellings (Finnish Statistical Yearbook of Forestry 2014). The stumpage price (i.e. price per m^3 of standing trees), determined separately for each sale, is somewhere between the buyer's maximum willingness to pay and the seller's minimum willingness to accept (Omwami 1986). Kolis et al. (2014), examining the effects that sale and site-specific characteristics have on the stumpage prices paid to non-industrial private forest owners in Finland, concluded that (1) buyers take differences in harvesting costs into account when making purchase offers, and (2) buyers are more interested in stands with a high percentage of sawlogs.

Bucking is a process in which the tree stem is divided into products based on the roundwood user's needs regarding products and their quality and dimensions. Optimization methods are used to recover the highest value for each stem with a given product price matrix (i.e. the unit price per length and diameter for each log dimension) (see Table 2) and the requested length-diameter distribution (Näsberg 1985; Malinen and Palander 2004).

When using cut-to-length methods, bucking decisions have to be made in the forest on the basis of the prices of and demand for timber assortments (Malinen et al. 2001). Different means of estimating timber assortments obtainable by cut-to-length methods have been proposed for use in boreal forests. For example, Kangas and Maltamo (2002) used height and taper curve models together with diameter distribution models and calibration, whilst Malinen et al. (2001) used the non-parametric k Most Similar Neighbour (k-MSN) method based on existing stem databases that included timber assortment recoveries and bucking simulations for individual stems. Cut-to-length harvesters collect a large amount of data which can be used for stem databases. The decision support system needed in the Nordic cut-to-length method requires detailed pre-harvest information, which is used to allot specific timber assortments required for raw materials and to plan harvesting operations to satisfy production needs. Its most important attributes are the availability of a stem diameter distribution for each tree species present in a stand and of quality information. This type of detailed pre-harvest information is not commonly used in practice, however (Vauhkonen et al. 2014), because of its costly input data requirements.

There has been widespread discussion in the Finnish forest industry about the possibility of modifying timber pricing in a quality-based direction (see Malinen et al. 2014). This could significantly affect the timber market and the accuracy of the inventory information required from the forests (Kankare et al. 2014). Moreover, timber prices could be more precise and contain user-specific values for each forest product.

In the Nordic countries, stand-level forest inventories following a wall-to-wall approach (full-cover inventories) based on the use of airborne laser scanners (ALS) have been operational since 2002 (Næsset et al. 2004), although the application of ALS remote sensing methods to the estimation of forest stand characteristics had been studied prior to that time. For example, Hyyppä et al. (1997) used the individual tree detection (ITD) approach to estimate stem volume accurately, reporting a coefficient of variation of 26.5%. More recently, the extraction of forest variables has been divided into two categories: the area-based approach (ABA) and ITD (Kaartinen et al. 2012). They differ with respect to the unit to be estimated: in the ITD approach the forest variables are estimated at the tree level, whereas in the ABA mean forest variables are estimated at the plot (or grid cell or segment) level (Peuhkurinen 2011). The ITD approach requires denser ALS data than the ABA and it is effective for detecting trees in the dominant tree layer, whereas small, suppressed trees may remain undetected (Valbuena et al. 2014; Wang et al. 2016). Both approaches can be used to estimate complete tree lists (Hou et al. 2016).

Peuhkurinen et al. (2007) demonstrated that it is possible to obtain accurate sawlog volume estimates with an ALS-based ITD method, while Korhonen et al. (2008) showed that direct regression models based on laser-scanned canopy height metrics are capable of producing satisfactory estimates of sawlog volumes in coniferous forests on a local scale. Peuhkurinen (2011) studied the use of ALS-based forest inventory methods for retrieving the information needed for wood procurement planning, and also investigated the possibility of using ALS-based methods to estimate stand-level diameter distributions. Moreover, Peuhkurinen (2011) examined the possibilities for using harvester-collected data as validation data and as an auxiliary data source in an ALS-based forest inventory, and developed and tested ALS-based methods for estimating theoretical and actual sawlog recoveries. Barth et al. (2015) compared the results of bucking simulations based on ALS data to actual production data from harvesters, and demonstrated ALS-based inventory data can improve the prediction of product recovery.

In addition, ALS has been used to estimate tree quality properties. Maltamo et al. (2009), for example, pointed out that variables describing tree quality were highly accurate when ALS-based variables were used together with non-parametric k-MSN modelling. However, this kind of approach requires detailed reference data, which are seldom available.

Although detailed data including tree lists can be collected by means of field measurements, this approach has been found to be too laborious and expensive, and the same also concerns field measurement methods based on sampling (Uusitalo 1995). Despite the fact that non-parametric methods utilizing stem-wise dimension data collected by cut-to-length harvesters (Malinen et al. 2001; Malinen 2003) and further external quality databases (Malinen et al. 2014) reduce costs, they still require some input data to be collected in the field. Wood procurement planning and the purchasing of timber will be conducted more and more in a digitalized environment in the future, without possibilities for visiting all potential stands, and there is an emerging need to develop methodologies which offer information on the properties and value of a stand and the products obtainable from it. Such methodologies would help to reduce or remove the need for stand visits.

The underlying hypothesis for this research was that useful estimates of wood paying capability (WPC) could be obtained if remote sensing data were used together with reference stem quality information, leading to more efficient buying performance. A methodology is thus presented here for defining the value of harvestable timber stands based on their product yield. Dimensions, quality and timber assortments for Scots pine (*Pinus sylvestris* L.) were considered when estimating the value of a given stand. ALS and colour-infrared airborne spectral data were used to determine the value indicators, the goal being to present a sound methodology for timber stand valuation that could be used as a decision support tool by either timber buyers or sellers.

Materials and methods

The area of interest is located close to the rural district of Kiihtelysvaara in the province of Northern Karelia in Eastern Finland (62°31'N; 30°10'E; 130-153 m above sea level; 707 ha) (Fig. 1). The main tree species in this area is Scots pine (*Pinus sylvestris* L.), representing almost three-fourths of the total wood volume. Norway spruce [*Picea abies* (L.) H. Karst] is the second major species, followed by a minor proportion of broadleaved species, mainly birches (*Betula* spp.).

Since the proportions of Norway spruce in Nordic forests are highly dependent on the dimensions of the stems, Norway spruces are typically bucked by cut-to-length harvesters by means of "automated cutting", emphasizing only the length-diameter distribution of the logs. Moreover, the main defect affecting the value of Norway spruce, root rot [*Heterobasidion annosum* (Fr.) Bref.], is not visible externally. The value of Scots pine, on the other hand, is highly dependent on the branchiness of the stems and external effects (Uusitalo et al. 2004). The proportion of the third species, birch, was very low in this area, and thus only Scots pine was chosen for investigation.

The field survey data consisted of a stratified sample of 79 square-shaped plots, the location of which was determined subjectively in order to guarantee that the sample covered the full range of variability in the forest. The measurements were made in May and June 2010. The sample plots varied in size between 20 × 20, 25 × 25 and 30 × 30 m (i.e. 0.04 ha, 0.0625 ha and 0.09 ha, respectively) according to their stand development class. Height, diameter at breast height (DBH) and species (Scots pine, Norway spruce or birch) were recorded for all the trees inside the plots with a DBH above 4 cm or height above 4 m. The main properties of the field data are presented in Table 1. 63 of the plots were situated within an area owned by UPM-Kymmene Oyj, while the remaining 16 plots belonged to 8 separate private owners (Valbuena et al. 2016).

The spectral data were acquired on 31 May 2009 using a Vexcel camera at a flight elevation of 7500 m above ground level (AGL). The ground sample distance (i.e. spatial resolution) was 45 cm.

The ALS data were collected on 26 June 2009 using an Optech ALTM Gemini laser scanning system from 600 m AGL with a field of view of 26° and a swath width of 320 m. The sensor was pointed in the nadir direction. Side overlap was 55%. The pulse repetition frequency was 125 kHz, which resulted in an average point density of 11.9 pulses·m^{-2}. Multiple echoes were recorded for each pulse. The last ALS echoes were classified as ground data and interpolated into a Digital Terrain Model with 1 m resolution. The LAS files were pre-processed to alter the Z value to represent elevation AGL (dZ files). Echoes with heights above ground lower than 1 m and higher than 40 m were masked out, since the low echoes were considered to be mainly reflected from the ground and the high ones to be too elevated to represent the vegetation of that area. ALS metrics (Næsset 2002) were calculated at plot and grid cell level using the remaining echoes. Metrics at the grid cell level were computed over a regular grid of 25 m × 25 m cells covering the entire scanning area.

A list of Scots pine stems was estimated with the ABA at grid level for the whole area by means of the ALS data and spectral data (Fig. 2), using the field data as a reference. The method generated an estimate of the entire DBH and height frequency distribution in discrete 2 cm-wide DBH classes, i.e. $y_{DBH} = \{N_{DBH=2}, N_{DBH=4}, \ldots, N_{DBH=50}\}$, $y_{\bar{H}} = \{\bar{H}_{DBH=2}, \bar{H}_{DBH=4}, \ldots, \bar{H}_{DBH=50}\}$ (where $N_{DBH=i}$ was the proportion of stems in DBH class i, and $\bar{H}_{DBH=i}$ the mean height of the stems for the DBH class i). The error-level estimates of the predicted stand density, DBH and height were obtained using k-MSN prediction and the leave-one-out method. K-MSN was also the statistical method used in the tree list estimation, where the 2 most similar neighbours were used to estimate the stand density, and the most similar neighbour for estimating the DBH and height frequency distributions, to avoid averaging between trees. For the final tree list, the trees in a given DBH class were divided evenly within that class to an accuracy of 1 mm.

A geometric intersection between the plots and the overlapping grid cells was computed for validation purposes, and a tree list was generated by weighting the number of trees estimated in the intersected grid cells by their area.

In a classical sampling survey a sample is planned within a population, and if there are plots outside the target population two different populations are considered. In practical timber procurement mapping, the large area covering all the plots has different characteristics compared to the situation in the small subareas. When plot based information are transferred from a large area to a subarea during the estimation process, design bias can easily appear because the populations are different. The plots used here were not exclusively from the area to be evaluated, and thus the effect of design bias at the plot level was examined by using under- and over-predictions of one standard deviation of the estimated DBH. For this purpose two more sets of tree lists were generated: one containing under-prediction (i.e. the estimated DBH minus one standard deviation) and the other over-prediction (the estimated DBH plus one standard deviation) (Fig. 2).

The tapering of the stems was calculated using taper curve models expressed as a function of tree species, DBH and tree height (Laasasenaho 1982). The heights of the stumps were calculated using the models of Laasasenaho (1982) for stump height as a function of tree species and DBH (Fig. 2).

Characteristics of external quality that affect bucking were estimated for each Scots pine stem using the stem quality database and the MSN method (Malinen et al. 2014) (Fig. 2). The database includes stem quality data for over 13 000 trees measured for dimensions and assessed for stem quality affecting bucking, based on visual estimation of the occurrence of technical defects (sweeps, scars, branchiness, crooks, etc.) and measuring their effective lengths. Technical defects in the target stems were estimated by selecting the most similar stem from the quality database by reference to the stand variables, tree DBH, and stem height (Malinen et al. 2014). The volume and value of the group of stems to be evaluated were assessed using a bucking-to-value simulator along with the stem quality database. The bucking simulations divided the tree stems into typical products of the Finnish forest industry, namely grade A butt logs, small-diameter logs, other sawlogs and pulpwood.

The search variables were the following: tree species, area, species proportion, effective temperature sum (threshold temperature +5%), DBH, dominant height, map coordinates (latitude and longitude) and basal area. All the variables describing the growing stock were expressed per species (Malinen et al. 2014). As stated by Malinen et al. (2001), the mean tree variables are the most important search variables, and the other variables are of minor significance.

The minimum top-end diameter for Scots pine was 21 cm for grade A butt logs, 15 cm for other sawlogs, 12 cm for small-diameter logs, and 7 cm for pulpwood, while the minimum length was 3.7 m for other sawlogs and small-diameter logs and 2.8 m for grade A butt logs and pulpwood. The theoretical sawlog volume, which is the stem volume exceeding the minimum diameter, was calculated using the taper curve models of Laasasenaho (1982), with a minimum diameter of 15 cm and a minimum length of 3.7 m (Table 3). The unit prices for the timber assortment volumes (TAV) were 58 €·m^{-}

^{3} for grade A butt logs, 55 €·m^{-3} for other sawlogs, 25 €·m^{-3} for small-diameter logs and 17 €·m^{-3} for pulpwood. All the volumes considered here are solid volumes over bark, and the total volumes are calculated from the stump to the top of the stem. The prices were typical stumpage prices paid in Finland in week 4 of 2017 (Roundwood prices for standing sales 2017).

The price lists used in the bucking simulations were based on WPC, which is considered the residual value that the forest product or industrial process can “pay” after all costs (excluding wood) have been deducted from the sales prices (Paavilainen 2002). An example of the tables used for calculating WPC (€·m^{-3}) for Scots pine sawlogs is presented in Table 2.

Timber assortments were calculated for four scenarios (tree lists), each produced using one of the following data sets: (1) the measured field data, (2) the estimated data, and when testing for design bias the evaluated tree list with under-prediction (3) or over-prediction (4) of the estimated DBH by one standard deviation. The timber assortments produced from each of those scenarios are presented in Table 3. For validation purposes, this research is focused on the tree lists from the field plots and the estimated tree lists from the grid cells that overlapped geometrically with them (Fig. 2).

The precision of the method was calculated in terms of the relative root mean squared error (RMSE%):

$$(1)\ \text{RMSE\%} = 100 \times \frac{\sqrt{\frac{\sum_{j=1}^{n}(y_{ij} - \hat{y}_{ij})^2}{n}}}{\bar{y}_i}$$

where y_{ij} is the measured value of the variable i in stand j, $\hat{y}_{ij}$ is the estimated value of the variable i in stand j, and $\bar{y}_i$ is the average of the measured values of the variable i.

The accuracy of the method was measured in terms of the bias of the estimates as follows:

(2) $\mathrm{BIAS} = \frac{\sum_{j=1}^{n}(y_{ij} - \hat{y}_{ij})}{n}$

The RMSE%, bias and standard deviation between the measured and estimated values were calculated for the timber assortments in order to compare volumes, WPC and values for: the field data versus the estimated data (case A), the field data versus combined data for the under-estimated, over-estimated and normal estimates (case B).

Results

Prediction error statistics for volumes, values and wood paying capabilities for the various timber assortments are shown in Tables 4, 5, 6 and 7. Table 4 does not contain the total values, as these were constant in all the cases: volume = 146.2 $m^3 \cdot ha^{-1}$; RMSE = 52.0%; bias = -8.4 $m^3 \cdot ha^{-1}$; standard deviation = 76.1 $m^3 \cdot ha^{-1}$. The maximum theoretical sawlog (scenario 1) was only used for volume.

Tables 4, 5 and 7 show the difference between the maximum theoretical volume and value, and the volume and value based on bucking simulation, arising from the effect of the log length constraints. Use of the bucking objectives reduced the sawlog volume by 1.0%. The bucking estimates based on dimensions and external quality (scenario 3) produced 30.0% less sawlog volume and 30.9% less sawlog value than those based only on dimensions (scenario 2). Due to the lower small end diameter requirements of small-diameter logs, the total volume of all sawlog assortments combined (i.e. the sum of the volumes of grade A butt logs, sawlogs and small-diameter logs in scenario 4) was 25.4% higher than the sawlog volume based on external quality without grade A butt logs and small-diameter logs (i.e. the sawlog volume in scenario 3). In the same way as for volume, the total value of the combined sawlog assortments (scenario 4) was 22.5%

higher than the sawlog value based on external quality without grade A butt logs and small-diameter logs (scenario 3).

The RMSE% of the bucking estimates for sawlog volume when quality estimation was included (scenario 3) was 11.2 percentage points (pp) higher than when quality was not considered (scenario 2), and 12.2 pp higher for sawlog value. In the case of the estimates for both pulpwood volume and value, the RMSE% when considering quality (scenario 3) was 6.0 pp higher than when the bucking estimates were based only on dimensions (scenario 2) (Tables 4 and 5).

Tables 8 and 9 show the effect of design bias at the plot level on volumes, values and WPC both excluding and including quality estimation. When quality estimation was excluded, the bias for volumes and values was negative for sawlogs but positive for pulpwood (Table 8); whereas when quality estimation was included it was negative for both sawlogs and pulpwood (Table 9). When quality estimation was included, the RMSE% of the bucking estimates for the differences between the field data and the data combined from under-estimated, over-estimated and normally estimated results (case B) was 2.5 pp lower than the RMSE% of the bucking estimates for the differences between the field data and the estimated data (case A) for sawlog volume, and 3.4 pp lower for sawlog value. When only dimensions were considered, the RMSE% was 5.9 pp higher for case B than for case A where sawlog volume was concerned, and 7.6 pp higher for sawlog value. Inclusion of the quality estimate for pulpwood did not change the RMSE% for volume and value with respect to the bucking estimate obtained only with dimensions, the RMSE% of case B being 11.8 pp higher than that of case A for the bucking estimate including quality and 6.2 pp higher for the bucking estimate obtained using only dimensions.

The residual errors in sawlog volume (Fig. 3A), sawlog value (Fig. 3B), pulpwood volume (Fig. 3C) and pulpwood value (Fig. 3D) when excluding or including the quality estimates are presented in Fig. 3. Figs. 3A and 3B show the residual errors decreased as the sawlog volume and value increased. Figs. 3C and 3D show that pulpwood follows a similar trend to that seen in sawlogs, but the relative errors were larger for pulpwood, especially for pulpwood value.

Discussion

The method presented here is intended to support wood procurement practices. There is an increasing need for information on diameter distributions among private forest companies. Several research papers have targeted this need, studying the estimation of diameter distributions, but the effect of quality and value on the diameter distribution estimates has not been studied so extensively (see Kotamaa et al. 2010). Such a method would have the potential to make roundwood markets more efficient by supplying each roundwood user with more suitable timber for processing.

The focus of this research was on presenting a workable method and examining its ability to measure value and WPC accurately. The plot data were measured with high precision to allow full development and evaluation of the method, but as it does not conform with the typical operational methods used today, no comparison with traditional methods is included. A stem quality database can be used to replace expensive measurements, and field work can be partially replaced by remote sensing data.

ALS data detect well trees in the dominant tree layer, which constitute the majority of the total volume (Peuhkurinen et al. 2011). In this sense the method supports decision-making and provides information on which stands are of the greatest interest and should be more carefully assessed.

The results of the bucking of maximum theoretical sawlog volumes excluding quality estimation (scenario 1) and of sawlog and pulpwood volumes excluding quality estimation (scenario 2) are alike (Table 4), and the RMSE% results for volumes and values are quite similar, as seen in Tables 4 and 5. This is partially caused by the fact that the value estimate is a weighted version of the volume estimate (calculated by multiplying the volume by the unit prices for the TAV). The RMSE% becomes slightly higher if quality estimation is considered. In the approach that considers four timber assortments (scenario 4), the bucking objectives included grade A butt logs and small-diameter sawlogs in addition to conventional sawlogs and pulpwood, and the more complicated bucking objectives certainly introduce some error into the estimates. On the other hand, raising the number of timber assortments increased the weighting on external quality. The RMSE% values show that the variables used are quite efficient in predicting dimensions but slightly less so in predicting log quality. On the other hand, the estimates that take account of quality include additional usable information for the decision-maker, even though their predictive ability is poorer. The estimates are more robust for pulpwood than for sawlogs (the errors are smaller), but RMSE% increases progressively as we introduce (1) bucking, (2) quality and (3) assortments. The presented method allows the recognition of grade A butt logs, the value of which is high, thus increasing the value and WPC of this timber assortment.

WPC incorporates external quality and the size distribution of logs, and its estimates (Tables 6 and 7) are more precise than those for volume and value (Tables 4, 5 and 7) overall and for sawlogs and similar for pulpwood. This is because sawlog volume and value are affected only by the proportion of sawlogs by volume, while WPC is also affected by the size of the logs: larger logs from longer and thicker trees are more valuable than small logs from shorter and thinner ones. Moreover, this method uses ALS data, which are more successful in assessing large trees than small or suppressed trees, which are not easily detected by ALS techniques (see Peuhkurinen et al. 2007). Also, WPC does not involve any volume estimation error. WPC is seldom used, however, as such values are rarely available and require bucking simulation, which is not commonly used in ALS survey.

The differences between case A and case B in Tables 8 and 9 are very small, which means this is a precise and robust method. The method underestimates sawlogs and overestimates pulpwood when quality is not an issue (Table 8) and underestimates both when quality is considered (Table 9). It thus provides a conservative estimate for the total value of the stand. The database of stem dimensions had been collected from a large geographical area, of which the test site is a rather small part. Thus, a small-area approach of this kind is evidently more sensitive to local differences.

The sawlog and pulpwood volumes and values that include quality involve a more complex estimation process and inevitably lead to larger estimation errors than those which exclude quality. It would have been useful to compare estimates including quality with actual harvesting recovery data, but figures of the latter type are seldom available. The problem in our comparisons is that the reference values are based on estimates for measured trees, and the RMSE% and bias may be underestimated. The errors in stand-wise estimates are thought to be smaller than those in plot-wise estimates due to noise caused by the high variability between stem-wise external quality estimates. RMSE% is a variable that is affected if some errors are really high.

Hou et al. (2016) estimated the ABA-derived diameter distribution in the same forest area as was used for this research but without applying any species identification procedure in k-MSN and obtained the following RMSE% results for total, sawlog and pulpwood volumes, respectively: ~35%, ~40% and ~65% for Scots pine, ~90%, ~85% and ~190% for Norway spruce, and ~180%, ~230% and ~215% for deciduous species. When predicting DBH distributions in this way they set k = 3 and used 1 cm-wide DBH classes. In our case k was set to 1 to avoid averaging between trees, and 2 cm-wide DBH classes were used to ensure continuous DBH distributions with a relatively small number of trees per plot. More accurate estimates of DBH distributions could be achieved by examining more field plots. In this study, standard operational ALS data processing methodology was used and the approach presented by Hou et al. (2016) could slightly improve results. The forest concerned is predominantly pine and is a good area for studying the effect of using diameter distributions and product yield simulations, since the role of tree species is minimized even though it is still present to some extent.

It is difficult to identify tree species directly from ALS measurements (McRoberts et al. 2010; Vauhkonen et al. 2012), although multispectral and hyperspectral optical imagery may be used in an automated or semi-automated procedure to estimate species composition (Clark et al. 2005). Multispectral imagery usually has three or four broad bands in the red, green, blue and infrared parts of the spectrum, while hyperspectral imagery has dozens or even hundreds of narrow, contiguous spectral bands. Simultaneous collection of data from different sources such as ALS and multispectral imagery or ALS and hyperspectral imagery has gained in popularity in recent times (see Valbuena et al. 2013; Cook et al. 2013), which will allow the acquisition of these to become cost-efficient. Laser data provide accurate height information and support information on crown shape and size, while optical images give more details regarding spatial geometry and colour that can be used to classify tree species (Hyyppä et al.

2008). This study would have benefited from hyperspectral data being available instead of multispectral data (Table 1). The purpose here, however, was simply to present the methods and to improve species detection later on.

Haara and Korhonen (2004), when estimating stem volume with a field inventory at the compartment level, reported the following RMSE% results for Scots pine: 29.3 for total volume; 52.0 for sawlogs; and 30.8 for pulpwood, and later Korhonen et al. (2008), who used ALS data to estimate theoretical sawlog volumes for 14 coniferous stands where the tree species and the diameter distribution were known, obtained an RMSE% of 9.1 for Scots pine and spruce at the stand level. Malinen et al. (2014) used empirical data from sample plots to assess the performance of a decision support tool for estimating of timber assortment recovery volumes and arrived at RMSE% values of 6.67 for grade A butt logs, 7.14 for other sawlogs, 2.48 for small-diameter logs and 7.09 for pulpwood. Siipilehto et al. (2016), who estimated stem volumes using a grid-level ABA based on ALS data and they compared these with tree taper data measured and recorded by the harvester's measurement systems during the final cut, reported RMSE% values of 41.1 for total Scots pine volumes, 40.1 for sawlogs and 52.8 for pulpwood.

In conclusion, it may be said that tree species estimation is the main challenge. While it is easy to estimate total volumes using ALS, estimating volumes per species becomes much harder, and the relative errors increase further when timber assortments are estimated. To resolve this issue, ALS data should be combined with multispectral or hyperspectral images. Tree species recognition should be improved by directing attention to areas where species diversity is higher. The present method can be applied in practice in single-species forest stands, where the tree species is known, as is commonly the case in the Nordic countries. WPC values for pulpwood can be estimated with RMSE of 32.7% by this method, and for sawlogs with RMSE of 38.5-52.1%.

Although field estimation is more reliable than remote sensing methods, the cost-efficiency of approaches supported by the latter can render them sufficient for practical planning operations.

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References

Barth, A., Möller, J.J., Wilhelmsson, L., Arlinger, J., Hedberg, R., and Söderman, U. 2015. A Swedish case study on the prediction of detailed product recovery from individual stem profiles based on airborne laser scanning. Ann. For. Sci. **72**(1): 47–56. doi:10.1007/s13595-014-0400-6.

Clark, M.L., Roberts, D.A., and Clark, D.B. 2005. Hyperspectral discrimination of tropical rain forest tree species at leaf to crown scales. Remote Sens. Environ. **96**(3–4): 375–398. doi:10.1016/j.rse.2005.03.009.

Cook, B.D., Corp, L.A., Nelson, R.F., Middleton, E.M., Morton, D.C., McCorkel, J.T., Masek, J.G., Ranson, K.J., Ly, V., and Montesano, P.M. 2013. NASA goddard's LiDAR, hyperspectral and thermal (G-LiHT) airborne imager. Remote Sens. **5**(8): 4045–4066. doi:10.3390/rs5084045.

Finnish Statistical Yearbook of Forestry 2014. 2014. Finnish Forest Research Institute. Tampere, Finland. pp. 1–426. Available from www.metla.fi/julkaisut/metsatilastollinenvsk/ [accessed 28 April 2017].

Haara, A., and Korhonen, K.T. 2004. Kuvioittaisen arvioinnin luotettavuus. Metsätieteen Aikakauskirja. **4**: 489–508 (in Finnish). Available from http://www.metla.fi/aikakauskirja/full/ff04/ff044489.pdf [accessed 28 April 2017].

Helstad, K. 2006. Managing timber procurement in Nordic purchasing sawmills. PhD dissertation, School of Technology and Design, Växjö University, Sweden. Available from: http://urn.kb.se/resolve?urn=urn:nbn:se:vxu:diva-771 [accessed 28 April 2017].

Hou, Z., Xu, Q., Vauhkonen, J., Maltamo, M., and Tokola, T. 2016. Species-specific combination and calibration between area-based and tree-based diameter distributions using airborne laser scanning. Can. J. For. Res. **46**: 753–765. doi:10.1139/cjfr-2016-0032.

Hyyppä, J., Pulliainen, J., Hallikainen, M., and Saatsi, A. 1997. Radar-derived standwise forest inventory. IEEE Trans. Geosci. Remote Sens. **35**(2): 392–404. doi:10.1109/36.563278.

Hyyppä, J., Hyyppä, H., Leckie, D., Gougeon, F., Yu, X., and Maltamo, M. 2008. Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. Int. J. Remote Sens. **29**(5): 1339–1366. doi:10.1080/01431160701736489.

Kaartinen, H., Hyyppä, J., Yu, X., Vastaranta, M., Hyyppä, H., Kukko, A., Holopainen, M., Heipke, C., Hirschmugl, M., Morsdorf, F., Næsset, E., Pitkänen, J., Popescu, S., Solberg, S., Wolf, B.M., and Wu, J.C. 2012. An international comparison of individual tree detection and extraction using airborne laser scanning. Remote Sens. **4**(4): 950–974. doi:10.3390/rs4040950.

Kangas, A., and Maltamo, M. 2002. Anticipating the variance of predicted stand volume and timber assortments with respect to stand characteristics and field measurements. Silva Fenn. **36**(4): 799–811. doi: 10.14214/sf.522.

Kankare, V., Joensuu, M., Vauhkonen, J., Holopainen, M., Tanhuanpää, T., Vastaranta, M., Hyyppä, J., Hyyppä, H., Alho, P., Rikala, J., and Sipi, M. 2014. Estimation of the timber quality of Scots pine with terrestrial laser scanning. Forests **5**(8): 1879–1895. doi:10.3390/f5081879.

Kivinen, V.-P., Uusitalo, J., and Nummi, T. 2005. Comparison of four measures designed for assessing the fit between the demand and output distributions of logs. Can. J. For. Res. **35**(3): 693–702. doi:10.1139/x04-196.

Kolis, K., Hiironen, J., Ärölä, E., and Vitikainen, A. 2014. Effects of sale-specific factors on stumpage prices in Finland. Silva Fenn. **48**(3): 1–18. doi:10.14214/sf.1054.

Korhonen, L., Peuhkurinen, J., Malinen, J., Suvanto, A., Maltamo, M., Packalén, P., and Kangas, J. 2008. The use of airborne laser scanning to estimate sawlog volumes. Forestry, **81**(4): 499–510. doi:10.1093/forestry/cpn018.

Kotamaa, E., Tokola, T., Maltamo, M., Packalén, P., Kurttila, M., and Mäkinen, A. 2010. Integration of remote sensing-based bioenergy inventory data and optimal bucking for stand-level decision making. Eur. J. For. Res. **129**(5): 875–886. doi:10.1007/s10342-010-0357-4.

Laasasenaho, J. 1982. Taper curve and volume functions for pine, spruce and birch. In Communicationes Instituti Forestalis Fenniae. Helsinki, Finland. **108**: 1–74.

Malinen, J. 2003. Locally adaptable non-parametric methods for estimating stand characteristics for wood procurement planning. Silva Fenn. **37**(1): 109–120.

doi:10.14214/sf.514.

Malinen, J., and Palander, T. 2004. Metrics for distribution similarity applied to the bucking to demand procedure. Int. J. For. Eng. **15**(1): 33–40. Available from https://journals.lib.unb.ca/index.php/IJFE/article/view/9861 [accessed 26 September 2017].

Malinen, J., Maltamo, M., and Harstela, P. 2001. Application of Most Similar Neighbor Inference for Estimating Marked Stand Characteristics Using Harvester and Inventory Generated Stem Databases. Int. J. For. Eng. **12**(2): 33–41. Available from https://journals.lib.unb.ca/index.php/IJFE/article/view/9913/10098 [accessed 28 April 2017].

Malinen, J., Kilpeläinen, H., and Ylisirniö, K. 2014. Description and evaluation of Prehas software for pre-harvest assessment of timber assortments. Int. J. For. Eng. **25**(1): 66–74. doi:10.1080/14942119.2014.902686.

Maltamo, M., Peuhkurinen, J., Malinen, J., Vauhkonen, J., Packalén, P., and Tokola, T. 2009. Predicting tree attributes and quality characteristics of Scots pine using airborne laser scanning data. Silva Fenn. **43**(3): 507–521. doi:10.14214/sf.203.

McRoberts, R.E., Tomppo, E.O., and Næsset, E. 2010. Advances and emerging issues in national forest inventories. Scand. J. For. Res. **25**(4): 368–381. doi:10.1080/02827581.2010.496739.

Næsset, E. 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. Remote Sens. Environ. **80**(1): 88–99. doi:10.1016/S0034-4257(01)00290-5.

Næsset, E., Gobakken, T., Holmgren, J., Hyyppä, H., Hyyppä, J., Maltamo, M., Nilsson, M., Olsson, H., Persson, Å., and Söderman, U. 2004. Laser scanning of forest resources: the nordic experience. Scand. J. For. Res. **19**(6): 482–499. doi:10.1080/02827580410019553.

Näsberg, M. 1985. Mathematical programming models for optimal log bucking. Dissertation No. 132, Linköping University, Sweden. 201 p.

Omwami, R.K. 1986. A theory of stumpage appraisal. Silva Fenn. **20**(3): 189–203. doi:10.14214/sf.a15452.

Paavilainen, L. (*Editor*). 2002. Finnish Forest Cluster Research Programme WOOD WISDOM (1998–2001). Helsinki, Finland. pp. 1–441. Available from: https://www.tekes.fi/globalassets/julkaisut/wood_wisdom.pdf [accessed 28 April 2017].

Peuhkurinen, J. 2011. Estimating tree size distributions and timber assortment recoveries for wood procurement planning using airborne laser scanning. Dissertationes Forestales 126, University of Eastern Finland, Finland. doi:10.14214/df.126.

Peuhkurinen, J., Maltamo, M., Malinen, J., Pitkänen, J., and Packalén, P. 2007. Preharvest measurement of marked stands using airborne laser scanning. For. Sci. **53**(6): 653–661. Available from: http://www.ingentaconnect.com/content/saf/fs/2007/00000053/00000006/art00005 [accessed 28 April 2017].

Peuhkurinen, J., Mehtätalo, L., and Maltamo, M. 2011. Comparing individual tree detection and the area-based statistical approach for the retrieval of forest stand characteristics using airborne laser scanning in Scots pine stands. Can. J. For. Res. **41**(3): 583–598. doi:10.1139/X10-223.

Roundwood prices for standing sales 2017 (Metsäkustannus Oy) [online]. 2017. Available from https://www.metsalehti.fi/puunhinta/puunhinta/ [accessed 6 February 2017].

Siipilehto, J., Lindeman, H., Vastaranta, M., Yu, X., and Uusitalo, J. 2016. Reliability of the predicted stand structure for clear-cut stands using optional methods: airborne laser scanning-based methods, smartphone-based forest inventory application Trestima and pre-harvest measurement tool EMO. Silva Fenn. **50**(3): 1–24. doi:10.14214/sf.1568.

Uusitalo, J. 1995. Pre-harvest measurement of pine stands for sawing production planning. Publication 9, University of Helsinki, Finland. 96 p.

Uusitalo, J., Kokko, S., and Kivinen, V.-P. 2004. The effect of two bucking methods on Scots pine lumber quality. Silva Fenn. **38**(3): 291–303. doi:10.14214/sf.417.

Valbuena, R., De-Blas, A., Martín-Fernández, S., Maltamo, M., Nabuurs, G.J., and Manzanera, J.A. 2013. Within-species benefits of back-projecting airborne laser scanner and multispectral sensors in monospecific Pinus sylvestris forests. Eur. J. Remote Sens. **46**(1): 491–509. doi:10.5721/EuJRS20134629.

Valbuena, R., Vauhkonen, J., Packalén, P., Pitkänen, J., and Maltamo, M. 2014. Comparison of airborne laser scanning methods for estimating forest structure indicators based on Lorenz curves. ISPRS J. Photogramm. Remote Sens. **95**: 23–33. doi:10.1016/j.isprsjprs.2014.06.002.

Valbuena, R., Eerikäinen, K., Packalén, P., and Maltamo, M. 2016. Gini coefficient predictions from airborne lidar remote sensing display the effect of management intensity on forest structure. Ecol. Indic. **60**: 574–585. doi:10.1016/j.ecolind.2015.08.001.

Vauhkonen, J., Seppänen, A., Packalén, P., and Tokola, T. 2012. Improving species-specific plot volume estimates based on airborne laser scanning and image data using alpha shape metrics and balanced field data. Remote Sens. Environ. **124**: 534–541. doi:10.1016/j.rse.2012.06.002.

Vauhkonen, J., Packalén, P., Malinen, J., Pitkänen, J., and Maltamo, M. 2014. Airborne laser scanning-based decision support for wood procurement planning. Scand. J. For. Res. **29**(Supplement 1): 132–143. doi:10.1080/02827581.2013.813063.

Wang, Y., Hyyppä, J., Liang, X., Kaartinen, H., Yu, X., Lindberg, E., Holmgren, J., Qin, Y., Mallet, C., Ferraz, A., Torabzadeh, H., Morsdorf, F., Zhu, L., Liu, J., and Alho, P. 2016. International Benchmarking of the Individual Tree Detection Methods for Modeling 3-D Canopy Structure for Silviculture and Forest Ecology Using Airborne Laser Scanning. IEEE Trans. Geosci. Remote Sens. **54**(9): 5011–5027. doi:10.1109/TGRS.2016.2543225.

Table 1. Means, standard deviations, minima and maxima of plot attributes.

Variable	Minimum	Mean	Maximum	SD
DBH (cm)	8.1	15.0	28.4	4.0
Height (m)	8.7	14.4	24.1	3.3
Density (stems·ha^{-1})	467	1259	2875	566
Volume (m^{3}·ha^{-1})	79.5	197.6	502.2	73.6
Basal area (m^{2}·ha^{-1})	13.8	24.6	40.1	6.2
Pine basal area (m^{2}·ha^{-1})	0.0	18.3	33.5	8.8
Spruce basal area (m^{2}·ha^{-1})	0.0	8.2	40.0	12.2
Birch basal area (m^{2}·ha^{-1})	0.0	3.3	22.7	5.4

Note: DBH, diameter at breast height; SD, standard deviation.

Table 2. Example of a product price matrix used in calculating wood paying capability (€·m^{-3}) for Scots pine sawlogs.

Log length (m)	Log top-end diameter class (cm)								
	15	16	22	24	26	28	30	32	34+
3.7	57	62	66	70	73	76	78	79	80
4	62	67	72	76	79	83	85	86	87
4.3	67	72	77	82	85	89	91	92	93
4.6	69	73	79	84	87	91	93	94	95
4.9	70	74	80	85	89	92	94	96	96
5.2	71	76	81	86	90	93	95	97	98
5.5	71	76	81	86	90	93	95	97	98
5.8	71	76	81	86	90	93	95	97	98
6.1+	71	76	81	86	90	93	95	97	98

Table 3. Methodological differences between the calculation scenarios.

	Bucking method	Timber assortments	Quality included
Scenario 1	Maximum sawlog and pulpwood volumes	Sawlogs Pulpwood	No
Scenario 2	Log sizes with 30 cm interval	Sawlogs Pulpwood	No
Scenario 3	Log sizes with 30 cm interval	Sawlogs Pulpwood	Yes
Scenario 4	Log sizes with 30 cm interval	Grade A butt logs Sawlogs Small-diameter logs Pulpwood	Yes

Table 4. Volume prediction error statistics for the timber assortments at plot level.

		Scenario 1	Scenario 2	Scenario 3	Scenario 4
Sawlogs	Volume ($m^3 \cdot ha^{-1}$)	87.3	86.4	60.5	46.7
	RMSE (%)	81.3	81.7	92.9	89.9
	Bias ($m^3 \cdot ha^{-1}$)	-13.2	-13.0	-5.9	-8.2
	SD ($m^3 \cdot ha^{-1}$)	70.2	69.8	56.2	41.4
Pulpwood	Volume ($m^3 \cdot ha^{-1}$)	50.9	51.8	74.3	52.3
	RMSE (%)	32.2	31.7	37.7	49.4
	Bias ($m^3 \cdot ha^{-1}$)	2.0	1.8	-4.9	-4.6
	SD ($m^3 \cdot ha^{-1}$)	16.4	16.4	27.8	25.6

Table 5. Value prediction error statistics for the timber assortments at plot level.

		Scenario 2	Scenario 3	Scenario 4
Total	Value (€·ha^{-1})	7522.5	5853.5	6811.1
	RMSE (%)	80.8	85.0	80.8
	Bias (€·ha^{-1})	-1092.6	-634.0	-564.7
	SD (€·ha^{-1})	6021.1	4967.2	5509.5
Sawlogs	Value (€·ha^{-1})	6641.5	4590.3	3572.6
	RMSE (%)	90.7	102.9	96.1
	Bias (€·ha^{-1})	-1123.0	-550.3	-689.8
	SD (€·ha^{-1})	5956.4	4719.3	3385.7
Pulpwood	Value (€·ha^{-1})	881.1	1263.2	889.7
	RMSE (%)	31.7	37.7	49.4
	Bias (€·ha^{-1})	30.4	-83.7	-78.0
	SD (€·ha^{-1})	279.0	471.8	435.2

Table 6. Wood paying capability (WPC) prediction error statistics for the timber assortments at plot level.

		Scenario 2	Scenario 3	Scenario 4
Total	WPC (€·m^{-3})	47.9	36.1	42.3
	RMSE (%)	48.2	47.9	44.4
	Bias (€·m^{-3})	-6.5	-3.2	-2.8
	SD (€·m^{-3})	12.1	9.0	10.2
Sawlogs	WPC (€·m^{-3})	74.7	73.5	75.2
	RMSE (%)	38.5	44.2	52.1
	Bias (€·m^{-3})	-6.2	-6.8	-5.3
	SD (€·m^{-3})	3.2	3.5	3.2
Pulpwood	WPC (€·m^{-3})	17.0	17.0	17.0
	RMSE (%)	32.7	32.7	32.7
	Bias (€·m^{-3})	-1.1	-1.1	-1.1
	SD (€·m^{-3})	0.0	0.0	0.0

Table 7. Volume, value and wood paying capability (WPC) prediction error statistics for the detailed timber assortments in scenario 4 at plot level.

		Grade A butt logs	Sawlogs	Small-diameter logs	Pulpwood
Volume	Volume ($m^3 \cdot ha^{-1}$)	9.5	46.7	24.9	52.3
	RMSE (%)	209.5	89.9	42.8	49.4
	Bias ($m^3 \cdot ha^{-1}$)	2.2	-8.2	0.3	-4.6
	SD ($m^3 \cdot ha^{-1}$)	19.8	41.4	10.7	25.6
Value	Value (€$\cdot ha^{-1}$)	1004.5	3572.6	1344.3	889.7
	RMSE (%)	231.2	96.1	42.3	49.4
	Bias (€$\cdot ha^{-1}$)	183.3	-689.8	19.7	-78.0
	SD (€$\cdot ha^{-1}$)	2329.6	3385.7	572.0	435.2
WPC	WPC (€$\cdot m^{-3}$)	103.1	75.2	53.8	17.0
	RMSE (%)	137.5	52.1	41.7	32.7
	Bias (€$\cdot m^{-3}$)	15.3	-5.3	-4.8	-1.1
	SD (€$\cdot m^{-3}$)	7.3	3.2	3.1	0.0

Table 8. Plot-level precision and accuracy statistics excluding quality estimation.

		Volume A ($m^3 \cdot ha^{-1}$)	Volume B ($m^3 \cdot ha^{-1}$)	Value A (€$\cdot ha^{-1}$)	Value B (€$\cdot ha^{-1}$)	WPC A (€$\cdot m^{-3}$)	WPC B (€$\cdot m^{-3}$)
Total	RMSE (%)	52.0	53.7	80.8	87.0	48.2	46.6
	Bias	-8.4	-18.0	-1092.6	-2360.4	-6.5	-5.3
	SD	76.1	76.9	6021.1	6146.6	12.1	11.3
Sawlogs	RMSE (%)	81.7	87.6	90.7	98.3	38.5	45.5
	Bias	-13.0	-28.0	-1123.0	-2486.8	-6.2	-1.5
	SD	69.8	70.7	5956.4	6077.6	3.2	3.5
Pulpwood	RMSE (%)	31.7	37.9	31.7	37.9	32.7	32.7
	Bias	1.8	7.4	30.4	126.4	-1.1	-1.1
	SD	16.4	18.3	279.0	311.2	0.0	0.0

Note: A, differences between the field data and estimated data; B, differences between the field data and combined under-estimated, over-estimated and normal data; WPC, wood paying capability.

Table 9. Plot-level precision and accuracy statistics including quality estimation.

		Volume A ($m^3 \cdot ha^{-1}$)	Volume B ($m^3 \cdot ha^{-1}$)	Value A (€$\cdot ha^{-1}$)	Value B (€$\cdot ha^{-1}$)	WPC A (€$\cdot m^{-3}$)	WPC B (€$\cdot m^{-3}$)
Total	RMSE (%)	52.0	53.7	85.0	82.8	47.9	46.1
	Bias	-8.4	-18.0	-634.0	-830.5	-3.2	-0.6
	SD	76.1	76.9	4967.2	4808.5	9.0	8.4
Sawlogs	RMSE (%)	92.9	90.4	102.9	99.5	44.2	54.6
	Bias	-5.9	-5.3	-550.3	-571.7	-6.8	4.8
	SD	56.2	54.7	4719.3	4561.3	3.5	2.8
Pulpwood	RMSE (%)	37.7	49.5	37.7	49.5	32.7	32.7
	Bias	-4.9	-15.2	-83.7	-258.7	-1.1	-1.1
	SD	27.8	33.7	471.8	572.4	0.0	0.0

Note: A, differences between the field data and estimated data; B, differences between the field data and combined under-estimated, over-estimated and normal data; WPC, wood paying capability.

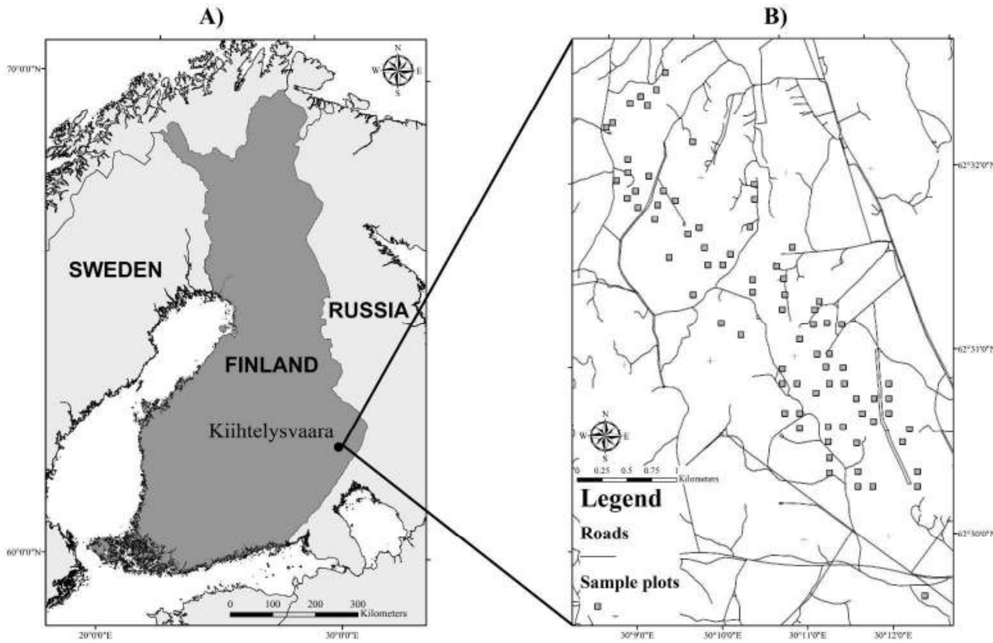

Fig. 1. A) Location of Kiihtelysvaara (●) within Finland (dark grey). B) Map of the Kiihtelysvaara forest area containing the sample plots.

294x188mm (300 x 300 DPI)

Fig. 2. Data processing steps.

379x233mm (300 x 300 DPI)

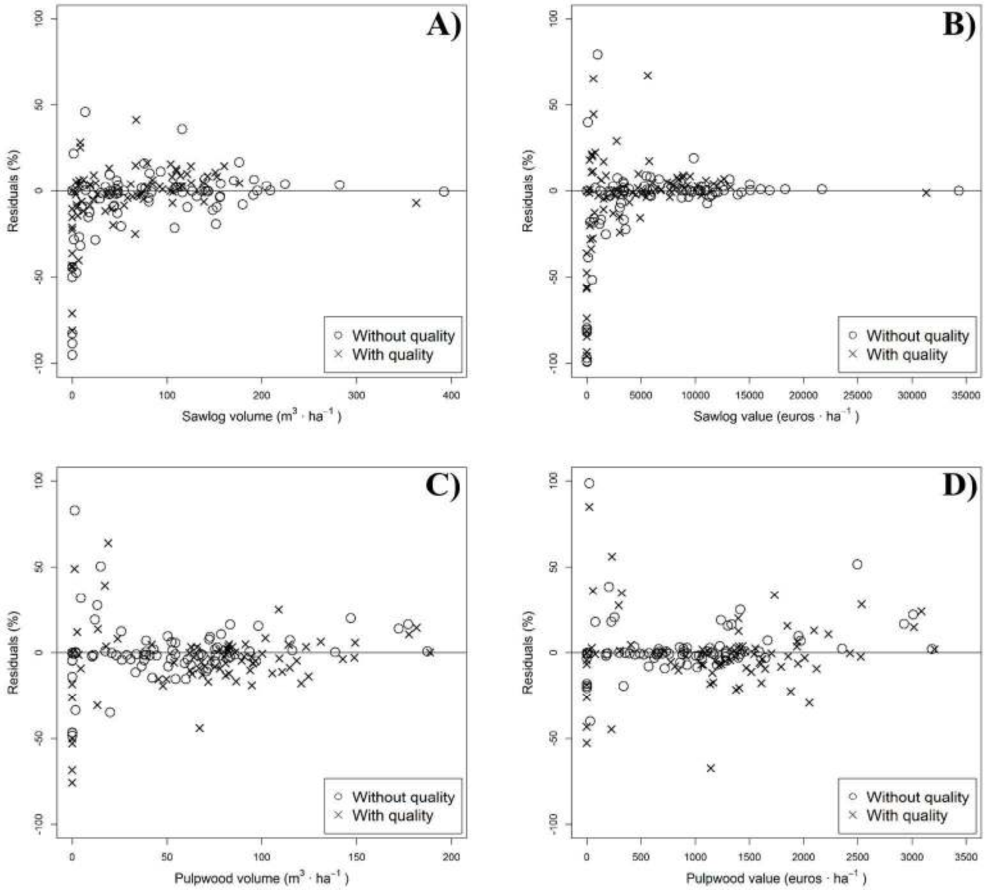

Fig. 3. Plot-level residual errors including and excluding quality estimation for: A) sawlog volume, B) sawlog value, C) pulpwood volume, and D) pulpwood value.

205x190mm (300 x 300 DPI)