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ORIGINAL PAPER

Assessing forest inventory information obtained from different inventory approaches and remote sensing data sources

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Abstract
• ***Context*** Evaluations of forest inventories usually end when accuracy and precision have been quantified.
• ***Aims*** We aim to value the accuracy of information derived from different remote sensing sensors (airborne laser scanning, aerial multispectral and hyperspectral imagery) and four alternative forest inventory approaches.
• ***Methods*** The approaches were (1) mean values or (2) diameter distributions both obtained by the area-based approach (ABA), (3) individual tree crown (ITC) segmentation and (4) an approach called semi-individual tree crown (SITC) segmentation. The estimated tree information was assessed and used to evaluate how erroneous inventory data affect economic value and loss due to suboptimal harvesting decisions. Field measured data used as reference come from 23 field plots collected in a study area in south-eastern Norway typical of managed boreal forests in Norway.
• ***Results*** The accuracy of the forest inventory was generally in line with previous studies. Our results show that using mean values from the area-based approach may yield large economic losses, while adding a diameter distribution to the area-based approach yielded less loss than the individual tree crown methods. Adding information from imagery had little effect on the results.
• ***Conclusions*** Taking inventory costs into account, diameter distributions from the area-based approach without additional information seems favourable.

Keywords Aerial imagery · Airborne laser scanning · Forest management inventory · Hyperspectral · Multispectral · Value of information

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Contribution of the co-authors Even Bergseng has performed economic analyses and lead the writing of the paper. Hans Ole Ørka performed the analyses of the remote sensing data and contributed in writing the paper. Erik Næsset and Terje Gobakken have designed the experiment and facilitated collection of all data and participated in writing the paper.

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1 Introduction

New and better information has a value. This value of information (VOI) can be calculated as the difference between the expected value of a given decision with additional information and the expected value of the same decision with only the prior information (Birchler and Bütler 2007). The VOI arises from the ability to make better decisions with new and additional information, and a rational decision maker would value this only as much as the expected improvement in decisions based on the new information. The role of VOI in planning of data acquisition is to ensure an optimal level of effort. For instance, the optimal number of sample plots in a field sample survey is achieved when marginal cost equals marginal benefit. Thus, the optimal amount of information is reached when further efforts yield information that are not worth their cost (e.g. Birchler and Bütler 2007). A similar optimization is needed with respect to the choice of forest inventory approaches and remote sensing data sources used for forest inventory.

The value of a forest inventory depends on its application, and the use of forest stand inventory data spans from valuation for stumpage sale to forest property valuation to strategic management planning. Forest management planning is a complex process, where decisions are related to different management levels (tree, stand, property, landscape, region etc.), planning levels (strategic, tactical and operational) and management objectives (timber, biodiversity, aesthetics, wildlife etc.). Until recent years, decision-support systems for forest management have been lacking affordable, detailed and precise input data covering large areas like a forest property or a municipality. The realm of available forest inventory approaches has been extended over the last few decades, especially with the introduction of forest inventory approaches based on airborne laser scanning (ALS; Hyyppä and Inkinen 1999; Næsset 2002; Næsset et al. 2004). This has facilitated increased use of decision-support systems that use information about the individual trees—at stand, property or regional level—as input (Gobakken et al. 2008; Wikström et al. 2011).

Forest owners (decision makers) usually characterize the quality of an inventory based on the correspondence between inventory volume and obtained timber volumes of harvested stands. Since the main objective of forest management inventories is to provide information that can be used for decision-making with respect to silvicultural treatments, an additional assessment step may be taken if a link between errors in the data, consequential incorrect treatment decisions and corresponding economic losses is established. This would provide valuable information, which may supplement considerations based on quantified errors only (cf. Eid et al. 2004).

ALS is considered the most accurate remote sensing technology for retrieval of detailed three-dimensional information on tree canopies and other biophysical characteristics essential for forest management inventories, such as mean tree height, basal area, and stem volume (Hyde et al. 2006; Hyyppä and Hyyppä 1999). ALS data is also used for species classification since crown allometry, branches, leaf structure etc. differ amongst species, although species information is still not easily obtained from ALS data (McRoberts et al. 2010). However, spectral information from passive remote sensing sensors is known to provide high separability of species (Brandtberg 2002; Carleer and Wolff 2004; Key et al. 2001), and especially the differences between coniferous and deciduous trees in the near-infrared wavelengths are well known. Multi-spectral images have been used for species classification for several years (Carleer and Wolff 2004; Haara and Haarala 2002), but recently, hyperspectral data have been shown to be superior to multispectral data for classification of tree species (Dalponte et al. 2012). Hence, the combination of ALS and spectral data might provide an important data acquisition strategy for information about trees and forests (McCombs et al. 2003; Ørka et al. 2012; Packalén and Maltamo 2006; Vauhkonen et al. 2012b).

Different forest inventory approaches using ALS have been described in previous research. In practical forest management inventories, the area-based approach (ABA, Næsset 2002) is most frequently used. In the ABA, forest properties are predicted for grid cells of typically 100–500 m^2 in size using regression models fitted on a sample of field plots with corresponding ALS observations and summarised to mean stand values (here denoted ABA-MV). Predicted stem frequency distributions (i.e. diameter distributions) could also be obtained using the area-based approach (here denoted ABA-DD; Gobakken and Næsset 2004, 2005). Furthermore, several approaches have been developed to provide tree-level information by individual tree crown delineation based on the ALS-derived canopy height model and then predict the properties of the crowns or segments such as stem diameter and tree height (e.g. Hyyppä and Inkinen 1999; Persson et al. 2002). Such approaches are collectively referred to as the individual tree crown (ITC) approach. The drawback using ITC is that only 30–70 % of the trees are detected, when commission errors are kept small (<20 %) (Kaartinen et al. 2012; Vauhkonen et al. 2012a). The reason is that ITC often is based on canopy height models, and thus, only the largest trees are detected, while suppressed trees are not found (Solberg et al. 2006). Uniform even-aged stands might obtain higher detection rates, but estimates of forest biophysical properties from ITC are hence often subject to systematic errors (Persson et al. 2002; Peuhkurinen et al. 2011). To account for this systematic error, a semi-individual tree crown (SITC) approach has been proposed (Breidenbach et al. 2010). Related methods are described by (Lindberg et al. 2008) and Flewelling (2008, 2009). The approach presented by Breidenbach et al. (2010) uses non-parametric estimation to assign tree-level information from a sample of field plots with individually located and measured trees to target segments and provide volume estimates that are less prone to systematic errors.

The different forest inventory approaches are associated with different levels of errors and costs. Peuhkurinen et al. (2011) compared ITC and area-based approaches (ABA) within the same test area in terms of their usefulness for estimating mean forest stand characteristics and tree size distributions. They found that average errors in volume and basal area did not differ significantly between the two approaches. ABA resulted in overall better accuracies when estimating the diameter and height of the basal area median tree and the number of stems, whereas ITC produced estimates with significant systematic errors for the number of stems and the mean tree size. Tree size distributions were estimated with slightly better accuracy using ABA. When testing with empirical data, Breidenbach et al. (2010) found the SITC approach to compare favourably to the ABA in terms of root-mean-square error (RMSE) for stem volume. A disadvantage of the ITC and SITC approaches is that they require high-pulse-density ALS data, causing an increase in costs compared to ABA. In Scandinavia, the ABA-MV, ABA-DD and ITC are promoted in the commercial market for forest management inventories and the decision as to what type of product is purchased is thus left up to the forest owners. Particularly in Norway, ABA-MV is used in almost all forest inventories.

When planning a new forest inventory, the decision maker typically strives for maximal accuracy within a given budget. However, statistical accuracy alone does not dictate the usefulness of the data (Ketzenberg et al. 2007). A growing literature is concerned with the value of forest information (Kangas 2010) and how different errors in inventory data may affect management decisions (Eid 2000; Eid et al. 2004; Kangas et al. 2011). The literature presents many different strategies for testing the effects of different inventory errors on management or finding a suitable level of inventory effort. In the current study, we focus on the value of information obtained from the different inventory approaches and remote sensing data sources, especially the additional use of spectral information to provide better species information.

The expected economic loss from a given data acquisition method has been analysed for different methods such as sampling-based forest inventory, traditional visual forest inventory, photo-interpretation-based forest inventory and ALS-based forest inventory (e.g. Borders et al. 2008; Eid et al. 2004; Holmström et al. 2003; Mäkinen et al. 2010). However, the VOI depends on the type of decision the information is used for. The first VOI study from forest inventory data based on ALS was carried out by Eid et al. (2004). They compared forest management inventory based on photo-interpretation and ABA-MV using a sample of field plots within each stand to represent the reference values. The results in Eid et al. (2004) were clear, while ABA-MV inventory cost was twice as large as for photo-interpretation; its total cost was still lower than those of photo-interpretation due to errors in the resulting forest data.

Eid et al. (2005) compared the diameter distribution in forest stands obtained from intensive systematic sample plot inventories, ABA-DD using ALS and a distribution predicted from models for diameter distribution in even-aged stands (Holte 1993; Mønness 1982) based on mean values obtained from manual photo-interpretation. Eid et al. (2005) found that the most intensive systematic sample plot inventories (10–14 plots per stand) generally provided the best results, followed by ABA-DD and subjective sample plot inventories, while photo-interpretation provided the poorest results. Laser scanning yielded approximately the same accuracy as the more extensive systematic sample plot inventories (three to five plots per stand).

Our objectives are to compare the accuracy of different forest inventory products and study the value of information when the inventory information is used for long-term planning (timing of final harvest in our case). We assess the VOI by quantifying the economic loss that arises when inventory data with different levels of accuracy is applied in management planning. We produce several sets of inventory data based on different inventory approaches (ABA-MV, ABA-DD, ITC and SITC) and remote sensing data (ALS and ALS data in combination with either multispectral or hyperspectral data). These data are used for valuing the forest land in the form of net present value (NPV) of expected future yields based on long-term management planning. This is done by employing the derived tree information in a decision support system in order to test the effects of incorrect information on forest management decisions, more specifically the timing of final harvest and the subsequent forest value. This is evaluated in terms of relative loss in net present value (NPV). We use field measured reference data (‘perfect information’) for comparison. In the following, we describe data material, inventory methods and methods for economic calculations before we present and discuss results.

2 Material and methods

2.1 Study area

The study area is located in the southern part of the boreal forest zone in south-eastern Norway, in the municipality of Aurskog-Høland (59°50′ N, 11°40′ E, 120–390 m a.s.l.). The total land area of Aurskog-Høland is 890 km^2, of which 75 % is covered by forest. The forest is managed and dominated by Scots pine (*Pinus sylvestris* L.) (50 %), Norway spruce (*Picea abies* (L.) Karst.) (35 %) and deciduous tree species (15 %), mainly birch (*Betula* spp.), but also aspen (*Populus tremula* L.), willow (*Salix* spp.) and some hardwood trees are found scattered in the landscape.

2.2 Field data collection

During the dormant season of 2007 and 2008, field data were collected on 23 circular sample plots. Eleven sample plots were located in spruce-dominated stands and the remaining 12 in pine-dominated stands. Seventeen of these plots were located in mature forest, and the remaining six plots were located in young productive forest. The size of the plots was 1,000 m^2, except for one plot in young productive forest where plot size was reduced to 500 m^2 due to a very high number of stems. On each sample plot, tree species, stem diameter at breast height (DBH) and tree coordinates were recorded for all trees with DBH ≥5 cm. For the dominant tree species, the height of two trees in each of five diameter classes—covering the entire range of diameters—was measured using a Vertex hypsometer. Up to five tree heights were measured for each secondary species. Secondary species trees were selected with probability proportional to their stem basal area. The heights of the unmeasured trees were estimated based on species-specific diameter–height curves developed from the measured trees; see Næsset et al. (2011) for further details. In total, 2,407 trees were recorded on the 23 plots. The plots are considered as stands in this study. The position of the trees was determined by measuring the azimuth and distance from the plot centre to the tree using a total station (Topcon Sokkia SET5F). Each plot centre was geographical referenced with a survey-grade global positioning system (GPS) and global navigation satellite system (GLONASS) receiver (Topcon Legacy E) with differential post-processing to get the highest available position accuracy. Random errors reported from the post-processing indicated an average error of 12 cm for the planimetric coordinates of the plot centres.

The volume of each tree was calculated by means of volume models for individual trees (Braastad 1966; Brantseg 1967; Vestjordet 1967), which are based on height and diameter as predictor variables. Total plot volume (V) was computed as the sum of the individual tree volumes. Mean plot diameter was computed as mean diameter by basal area (d_g) from diameter of all callipered trees and stem number was computed as number of trees per hectare (N). Basal area (G) was computed as basal area per hectare from the stem breast height diameter measurements. The field reference mean height of each plot was computed as the so-called Lorey's mean height (h_L), i.e. mean height weighted by basal area (Table 1).

The variables site index and stand age were obtained from an old stand data register, and these data were used for all inventory approaches and remote sensing data sources, including the field reference data.

2.3 Remote sensing data acquisitions

ALS data were acquired using the Optech ALTM 3100 laser scanning system (Optech, Canada) and colour infrared imagery (CIR) using the Applanix DSS 322 camera (Applanix, Canada) simultaneously. The CIR imagery consists of three bands covering the red, green and infrared portions of the spectrum. A separate acquisition of multispectral imagery covering red, green, blue and infrared parts (RGBI) was collected using the Vexcel UltraCam D sensor (Vexcel Imaging, Austria). Hyperspectral imagery was collected with the HySpex VNIR-1600 sensor (Norsk Elektro Optikk, Norway) in a third acquisition. The four resulting remote sensing datasets are referred to as ALS, CIR, RGBI and hyperspectral, respectively. Detailed sensor and acquisition settings appear in Table 2. The remote sensing data were acquired in different years, but the field plots were not influenced by harvest or mortality in the time period between data acquisitions.

Table 1 Summary of field reference data

Characteristic	Minimum	Maximum	Mean
h_L (m)	13.2	25.4	16.8
d_g (cm)	12.8	25.9	17.6
N (ha^{-1})	490	2,030	1,090
V (m^3 ha^{-1})	87.9	454.3	209.0
Tree species distribution			
N spruce (ha^{-1})	80	1,560	630.4
N pine (ha^{-1})	0	850	297.8
N broadleaves (ha^{-1})	0	590	162.2

h_L Lorey's mean height, d_g mean diameter by basal area, N number of trees, V volume

2.4 Forest inventory approaches

We use four different forest inventory approaches to derive forest and tree information:

(1) mean stand values (ABA-MV)
(2) diameter distributions (ABA-DD)
(3) individual tree crowns (ITC)
(4) semi-individual tree crowns (SITC)

The two first approaches represent the area-based approach (Næsset 2002) which has the grid cell as the estimation unit, but the level of detail in predicted values varies between the two area-based approaches. The two latter methods utilise canopy segments or tree crowns delineated from a canopy height model as the units where tree information is predicted. Forest biophysical properties are estimated from ALS data alone or ALS data in combination with one of the other remote sensing sources:

(1) colour infrared imagery (red-green-infrared) (CIR) acquired simultaneously with ALS
(2) multispectral RGBI imagery (RGBI) from a separate acquisition
(3) hyperspectral imagery (hyperspectral) from a separate acquisition

Thus, we produce 16 sets of forest data in addition to field reference data. Estimation procedures differ for the different data sets and combinations of data sources. These procedures are briefly explained below, but more details on the procedures and their application to the data may be found in Ørka et al. (2013). All estimates are cross validated using a leave-one-sample-plot-out procedure. Thus, to create predictions for each sample plot, information from the other 22 sample plots where used for creating models and classifications applied to the sample plot in question.

The accuracy of the predictions was assessed by relative mean difference and relative root-mean-square error (RMSE)

Table 2 Sensor and acquisition settings for remote sensing data

	ALS	CIR	RGBI	Hyperspectral
Date of acquisition	12 June 2006		29 June 2005	28 July 2008
Platform	Piper Navajo fixed wing		Piper Navajo fixed wing	Piper Chieftain fixed wing
Flying altitude (m)	800		3,100	1,500
Flying speed (ms^{-1})	75		80	70
Sensor	Optech ALTM 3100	Applanix DSS	Vexcel UltraCam D	HySpex VNIR-1600
Resolution (m)[a]	0.25	0.12	0.275/0.84	0.40
Pulse repletion frequency (kHz)	100	–	–	–
Scan frequency	70	–	–	–
Mean pulse density (m^{-2})	7.2	–	–	–
Swath width (m)	140	650	3,160	430
Spectral bands	1	3	4	160[b]
Spectral regions covered (nm)	1,064	500–600 600–700 800–960	390–530 470–660 570–690 670–940	410–980[b]

[a] Resolution refers to footprint size in diameter of ALS data and the ground sampling distance (GSD) for image data

[b] The band width was 3.7 nm

between field reference values and cross validated predicted values (Eqs. 1 and 2):

$$\text{Relative mean difference} = \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)}{n} / \overline{y} \tag{1}$$

$$\text{Relative RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{n}} / \overline{y} \tag{2}$$

where n is the number of plots, y_i is the field reference data value at plot i, $\hat{y}_i$ is the remote sensing-based prediction, and $\overline{y}$ is the mean of the field reference values. The absolute RMSE can be calculated by multiplying the RMSE by the mean field reference value.

2.4.1 Area-based approaches

For the two area-based approaches, the 23 sample plots were split into 250 m^2 subplots so that field observations were more similar to plot sizes and numbers used in practical forest management inventories using the area-based approach.

Area-based mean stand values (ABA-MV) Mean stand values were estimated with ALS and the area-based approach presented by Næsset (2002). Linear regression models were fitted for V, h_L, d_g, and G. No transformations of variables were applied. Variable selection was applied using the branch and bound search for the best subset implemented in the R package *leaps* (Lumley and Miller 2009). The models were constrained to include a maximum of five of the variables used by Næsset (2004) to avoid over-parameterization. Species proportions were obtained by estimating G for all species using the non-parametric random forest algorithm (Breiman 2001). The classification features were canopy density (Næsset 2004), echo proportions (single, intermediate, last) (Holmgren et al. 2008) computed from the ALS height distribution together with statistical features (maximum, mean, coefficient of variation, kurtosis, skewness and percentiles computed from the ALS intensity distribution) (Ørka et al. 2009). From the imagery, we derived mean of score values from a principal component analysis (PCA) which has proven favourable in other studies (Hill and Thomson 2005; Ørka et al. 2012). Other image features like original values, relative values and different ratios (Packalén et al. 2009; Waser et al. 2011) were tested in preliminary analysis; also in the current study, the PCA image features produced better accuracies. Number of stems for each species was computed from G, d_g and the proportion of G for each species.

Area-based diameter distributions (ABA-DD) Diameter distributions were obtained from ALS data using the area-based approach (Bollandsås and Næsset 2007; Gobakken and Næsset 2005) to model percentile-based diameter distributions (Borders et al. 1987). The empirical cumulative probability functions of each subplot were described with 14 percentiles (d_1, d_2, d_5, d_{10}, d_{20},…, d_{90}, d_{95} and d_{100}) of the basal area. Variable selection was carried out in the same manner as for ABA-MV, and the individual regression models were fitted as a system of models by seemingly unrelated regression. The cumulative basal area in each 2-cm-diameter class was calculated by linear interpolation and scaled with the stand basal area and divided on the basal area of the mean tree in each diameter class to obtain the number of stems in each class. The species-specific number of stems in each diameter class was obtained in a similar manner as for the ABA-MV approach. Species-specific and site index dependent local height-diameter relationships developed as part of an operational inventory in the area were applied to predict mean height in each diameter class. Mean diameter and height in each diameter class were used as input in volume models for individual trees (Braastad 1966; Brantseg 1967; Vestjordet 1967) and volume of all diameter classes were summed to stand volume.

Segment level approaches Individual tree crown delineation was performed using an adaptive segmentation method based on a Poisson forest stand model (Ene et al. 2012), which utilises the ABA-MV predicted number of stems for optimising the canopy height model smoothing. Tree crowns were extracted using a marker-based watershed algorithm (See Ene et al. 2012 for further details).

Individual tree crowns (ITC) The individual tree crown approach assumes that only one tree exists within one segment. Tree height and stem diameter were predicted from ALS data by linear models with maximum laser echo height and crown width as model terms according to Hyyppä et al. (2001). Furthermore, each segment was classified as spruce, pine, or deciduous using a balanced random forest classification (Breiman 2001; Chen et al. 2004) with the species of the tallest field tree inside each segment as reference class. The classification features were the same as for ABA-MV and ABA-DD but computed at segment level. Preliminary analysis revealed that PCA features also provided the best accuracies amongst different image feature groups suggested in the literature (Ørka et al. 2012; Packalén et al. 2009; Waser et al. 2011). Volume of each segmented tree was computed by means of volume models of individual trees (Braastad 1966; Brantseg 1967; Vestjordet 1967) and summed to stand level.

Semi-individual tree crowns (SITC) The SITC approach, as opposed to ITC, account for the fact that not all trees are found during the crown delineation (Breidenbach et al. 2010). Using SITC, field-measured trees were linked to segments and an imputation method was used to impute the information from the reference segment to segments without field measurements in the cross validation. We used the *k*-nearest neighbour imputation method to find reference segments for new targets, and the entire reference tree list was imputed. The tree list consists of stem diameter, tree height, volume and species, which were assigned to the target segment. Stand volumes were computed as the sum of imputed trees. The variables used were the same as for ITC species classification with additional ALS height metrics (maximum, mean, coefficient of variation, kurtosis, skewness and percentiles) and the PCA components accounting for 99 % of the variation in the hyperspectral imagery.

2.5 Economic calculations

We evaluate the value of the obtained data by assessing the loss in NPV due to incorrect timing of final harvests when using erroneous inventory data for decision-making by means of a long-term forest planning software (T, as described below). Loss in NPV owing to errors when the timing of the final harvest is considered is illustrated in Fig. 1. The curve shows the true NPV from final harvests in certain time periods. If it is assumed that field reference data provide information that enables the decision maker to make a 'correct' decision with final harvest at time T_{ref}, the result is maximum NPV (NPV_{ref}). If decisions are based on erroneous inventory data, harvest may be carried out at time $T_{\mathrm{approach1}}$ or $T_{\mathrm{approach2}}$ instead of T_{ref}. The resulting NPV losses can be calculated as the difference between NPV_{ref} and $NPV_{\mathrm{approach1}}$ or $NPV_{\mathrm{approach2}}$, respectively. Calculations as illustrated in Fig. 1 were performed for all stands and inventory approaches with the different combinations of remote sensing data sources as input.

The long-term forest planning software T (Gobakken et al. 2008) was used as a simulator for bioeconomic analyses in the current study. The software is based on biological as well as economic sub models for individual trees and performs long-term forest planning based on inventory data. The forest dynamics are described using species-specific submodels for the prediction of regeneration, recruitment, growth, mortality, timber value and harvest costs, with independent variables describing the individual trees, the forest stand and the site. Except for small trees (DBH <5 cm) single-tree distance-

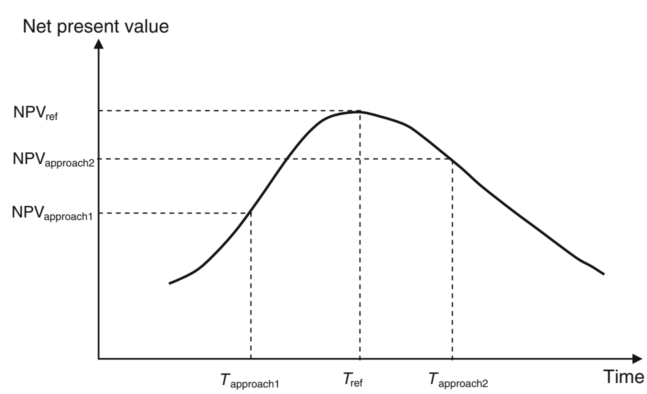

Fig. 1 Illustration of how net present value (*NPV*) losses may arise owing to erroneous inventory data. The curve shows the true NPV from final harvests in certain periods. If harvests are based on 'true' information, a 'correct' decision is made and maximum NPV is achieved. If harvests are based on estimated data from a certain inventory approach subject to errors, a lower NPV is achieved and NPV losses appear (Eid et al. 2004)

independent models for growth and mortality (Bollandsås 2007) are used. In contrast to other existing individual-tree simulators such as SILVA (Pretzsch et al. 2002) and MOTTI (Hynynen et al. 2005), the T software is designed to simulate many alternative treatment schedules for all stands in the planning area. For each management unit, the simulator produces all feasible combinations of user-defined treatment and regeneration options, i.e. alternative treatment schedules.

When individual tree data or diameter class data are not available from the inventory, T uses models for diameter distribution in even-aged stands (Holte 1993; Mønness 1982) to convert stand level data into diameter class data.

For planting, soil scarification and pre-commercial thinning user-defined costs are applied. Only the treatment decision 'timing of final harvest' was considered in this study. Based on the cash flow over the planning period and the value of the ending inventory, NPV is calculated and optimised for all treatment schedules. The value of the ending inventory is based on projections following predefined rules rather than being optimised. Details with respect to forest dynamics description, treatment options and definitions, cash flow and results are described in Gobakken et al. (2008).

In this study, forest management was optimised for 15 5-year periods, i.e. the planning period was 75 years, and all harvests were assumed to take place in the beginning of a period. Forest management rules in the analysis period were simple, with harvest/no harvest as the only decision. A real interest rate of 3 % and current timber prices for sawn wood and pulp wood and costs figures were applied.

3 Results

3.1 Forest inventory accuracy

3.1.1 Area-based mean stand values (ABA-MV)

The regression models explained 96.1, 92.7, 91.3 and 52.2 % of the variability in field reference V, G, h_L and d_g, respectively. The estimated mean values for V, d_g, h_L, and N were not significantly different from the field measured stand values, except for the number of stems for pine (Table 3). Furthermore, the relative RMSE values were approximately 10, 12, 9 and 37 % for V, d_g, h_L and N, respectively (Table 4). The models for species proportions for both area-based approaches (ABA-MV and ABA-DD) explained more than 78 % of the variability for spruce and pine but never exceeded 56 % for deciduous trees. Using ABA-MV, the explained variabilities were 78, 83 and 16 % for spruce, pine and deciduous trees, respectively. A slight increase occurred when using multispectral imagery for spruce (79–80 %) and pine (84–85 %), but the largest increase was obtained for deciduous trees (21–28 %). When using ALS and hyperspectral imagery combined, the explained variabilities increased to 88, 92 and 56 % for spruce,

Table 3 Mean stand differences in percent between field reference data and predicted values

Inventory approach	Remote sensing data sources	V	d_g	h_L	N	N spruce	N pine	N deciduous
ABA-MV	ALS	−0.4	1.3	−1.0	1.2	−7.2	38.0*	−33.2
ABA-MV	ALS+CIR	−0.4	1.3	−1.0	1.3	−7.5	38.5**	−33.0
ABA-MV	ALS+RGBI	−0.4	1.3	−1.0	1.2	−8.1	38.1**	−30.0
ABA-MV	ALS+Hyper.	−0.4	1.3	−1.0	1.4	−7.7	40.6**	−35.4
ABA-DD	ALS	3.2	9.0**	6.4*	20.3**	24.1**	−17.1	74.3**
ABA-DD	ALS+CIR	3.2	8.6**	6.4**	20.7**	25.1***	−18.2	75.3**
ABA-DD	ALS+RGBI	3.2	8.9**	6.5**	20.3**	24.8**	−16.8	71.0**
ABA-DD	ALS+Hyper.	3.4	8.5**	6.3*	20.5**	25.7***	−20.0	75.1**
ITC	ALS	26.9***	−24.4***	−5.8**	55.3***	61.0***	37.8***	64.9**
ITC	ALS+CIR	26.3***	−24.4***	−5.8**	55.3***	61.1***	39.7***	61.1**
ITC	ALS+RGBI	26.7***	−24.4***	−5.8**	55.3***	61.4***	36.9**	65.1**
ITC	ALS+Hyper.	26.3***	−24.4***	−5.8**	55.3***	62.0***	35.5***	65.4***
SITC	ALS	−3.3	−3.9	−0.4	8.1	11.1	0.9	9.9
SITC	ALS+CIR	−6.3	−3.7	−0.1	4.4	3.8	−9.5	32.4
SITC	ALS+RGBI	−2.8	−3.8	−0.2	8.4	15.2	−11.4	18.2
SITC	ALS+Hyper.	−8.5	−4.0	−0.5	4.1	6.1	−13.7	29.0

***p<0.001; **p<0.01; *p<0.05 (level of significance)

h_L Lorey's mean height, d_g mean diameter by basal area, N number of trees, V volume pine and deciduous trees, respectively. The RMSEs of estimated proportions were in the order of 0.17–0.20 for spruce and pine and 0.10–0.13 for deciduous trees. In all cases, hyperspectral imagery produced the lowest RMSEs and there were only minor differences between ALS alone and ALS plus the multispectral sensors.

3.1.2 Area-based diameter distributions (ABA-DD)

The estimated percentiles were not significantly different from the percentiles derived from the field measurements and the variability explained for the individual percentiles ranged from 8 % (d_1) to 56 % (d_{40}). All percentiles between d_{30} and d_{90} had R^2 greater than 50 %. RMSE ranged from 1.55 cm (d_2) to 5.77 (d_{100}). However, d_g, h_L and N were significantly underestimated using this approach (Table 3). Species-specific number of stems did not differ for pine trees but were underestimated for spruce and deciduous trees (Table 3). As illustrated in Fig. 2, the aggregated diameter distributions did fit quite well to the field measured distribution. The RMSEs obtained with ABA-DD are slightly larger than those obtained using ABA-MV, except for the estimates of N which are slightly smaller for ABA-DD.

3.1.3 Individual tree crowns (ITC)

The individual tree crown delineation identified 1,123 segments. Of these, 1,089 segments contained at least one field measured tree. In total, 53.4 % of the segments contained only one tree, 23.1 % two trees and 23.5 % contained three or more trees. Tree height models explained 98 % of the variation (R^2) and provided an RMSE of 66 cm. The stem diameter model was less accurate and provided an RMSE of 4.58 cm and 69 % explained variance (R^2). However, the ITC method only detected trees with large stem diameter (Fig. 2). Hence, V and N were highly underestimated and both d_g and h_L were overestimated (Table 3). The RMSE values on sample plot level were also influenced by these systematic errors (Table 4).

Species identification with ALS provided an overall accuracy of 74 % (κappa=0.56). Using addition of hyperspectral imagery increased the overall accuracy to 87 % (κappa=0.78). The addition of multispectral imagery provided overall accuracies of 79 % (κappa=0.65) and 81 % (κappa=0.67) for CIR and RGBI, respectively. Using multispectral imagery increased the accuracy for deciduous trees from 36 to 67–69 % but only slightly increased the class accuracies for spruce and pine. Hyperspectral imagery increased the classification accuracies for spruce and pine compared to multispectral imagery. Despite the increased accuracy for tree-wise comparisons with the error matrix from an overall accuracy from 74 to 87 %, the mean difference in species-specific number of stems did not improve notably (Table 3).

3.1.4 Semi-individual tree crowns (SITC)

The non-parametric imputation of tree list information was conducted using the four remote sensing data sources and resulted in tree lists with 92–96 % of the reference trees. The estimated N did not differ significantly from the field reference data. In addition, the obtained diameter distribution fitted quite

Table 4 Relative RMSE in percent between field reference data and predicted values

Inventory approach	Remote sensing data sources	V	d_g	h_L	N	N spruce	N pine	N deciduous
ABA-MV	ALS	9.9	12.1	9.0	37.1	47.5	73.7	133.6
ABA-MV	ALS+CIR	9.9	12.1	9.0	37.4	49.0	74.0	133.6
ABA-MV	ALS+RGBI	9.9	12.1	9.0	37.0	45.3	71.6	133.3
ABA-MV	ALS+Hyper.	9.9	12.1	9.0	37.3	51.8	75.4	103.6
ABA-DD	ALS	14.1	16.2	12.5	33.2	38.6	65.2	140.7
ABA-DD	ALS+CIR	14.2	16.0	12.3	33.2	39.7	65.0	137.9
ABA-DD	ALS+RGBI	14.2	16.3	12.5	32.9	39.8	63.4	134.9
ABA-DD	ALS+Hyper.	14.2	16.3	12.6	32.6	46.5	65.1	118.7
ITC	ALS	33.4	28.0	10.7	62.8	83.2	60.0	121.3
ITC	ALS+CIR	32.6	28.0	10.7	62.8	80.7	61.3	115.3
ITC	ALS+RGBI	33.1	28.0	10.7	62.8	83.5	58.9	105.5
ITC	ALS+Hyper.	32.6	28.0	10.7	62.8	81.9	55.3	102.9
SITC	ALS	28.0	14.3	8.0	26.7	39.3	47.8	144.8
SITC	ALS+CIR	32.5	12.1	7.8	25.9	33.2	45.7	113.5
SITC	ALS+RGBI	28.6	13.6	8.3	30.9	51.5	34.7	110.2
SITC	ALS+Hyper.	36.2	13.9	8.6	27.6	37.7	46.3	123.4

h_L Lorey's mean height, d_g mean diameter by basal area, N number of trees, V volume

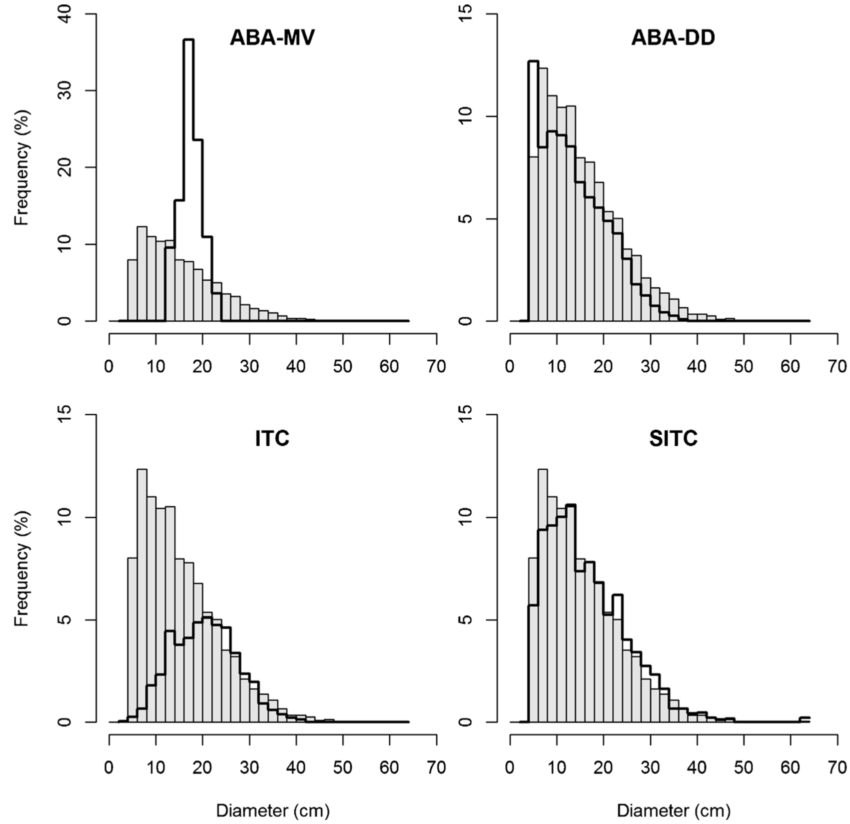

Fig. 2 Aggregated diameter distributions for all stands based on field measurements (*grey bars*) and the four inventory approaches (*ABA-MV* area-based approach, mean values, *ABA-DD* area-based approach, diameter distribution, *ITC* individual tree crown, *SITC* semi-individual tree crown) using ALS as the only remote sensing data source (*black line*). Note that the *y*-axis of ABA-MV is different from the others due to the effect of the mean tree on the frequencies

well with the field-measured diameter distribution (Fig. 2). Furthermore, V, d_g, h_L and species-specific number of stems were not significantly different from the field reference data (Table 3). The RMSE values obtained were at the same level as for ABA-MV except for V and N (Table 4).

3.2 Economic loss

The effects of erroneous inventory data on forest management, i.e. economic loss due to incorrect timing of harvest, are presented in Table 5. In these calculations, forest management decisions based on erroneous inventory data are applied to the field reference data. This mimics the typical situation in practical forestry, where planning and management decisions are based on inventory data, which may be erroneous, and then applied to the real forest, which may result in an economic loss due to incorrect decisions. The potential benefit of each method is then reduced loss due to better decisions.

When using field reference data as input to the long-term forest planning, the NPV was 6,069€ha^{-1}. The mean NPV loss when using inventory data from ABA-MV was around 5.4 % irrespective of remote sensing data sources. The maximum NPV loss for a single stand was 23 % and from 70 to 74 % of the stands had incorrect treatment timing in at least one of the 15 periods. ABA-DD, ITC and SITC had a loss in NPV from 1.0 to 1.9 %. The smallest losses were obtained for ABA-DD, with 1.0 % loss irrespective of the remote sensing data source. For ABA-DD, up to 48 % of the stands were harvested too early or too late in at least one of the 15 periods. Even if less than 40 % of the stands had incorrect treatment timing in at least one period and maximum loss for a stand was only 9 % for all ITC inventories, the NPV losses were between 1.2 and 1.4 %. For SITC, the maximum loss was 25 %. The results show that little value was added to the inventory by combining ALS data with auxiliary information from aerial imagery.

4 Discussion

4.1 Forest inventory accuracy

Even if our study is based on a limited number of sample plots located both in spruce- and pine-dominated forest, obtained accuracies were in general fairly good. In other studies and in practical inventories for forest management planning in Norway, separate models are usually developed for spruce- and pine-dominated forest.

The RMSE values obtained using ABA were higher than those typically found in Scandinavia (Næsset 2007). However, the results for the species proportions were in line or with

Table 5 Maximum and mean loss in net present value and number of stands with incorrect treatment timing when basing the timing of harvest on erroneous inventory data

Inventory approach	Remote sensing data sources	NPV loss compared to field reference data (%)[a]		Stands with incorrect timing of treatment (%)
		Max	Mean	
ABA-MV	ALS	23	5.4	74
ABA-MV	ALS+CIR	23	5.4	70
ABA-MV	ALS+RGBI	23	5.4	70
ABA-MV	ALS+Hyper.	23	5.5	74
ABA-DD	ALS	12	1.0	48
ABA-DD	ALS+CIR	12	1.0	48
ABA-DD	ALS+RGBI	12	1.0	48
ABA-DD	ALS+Hyper.	12	1.0	39
ITC	ALS	9	1.3	35
ITC	ALS+CIR	9	1.4	39
ITC	ALS+RGBI	9	1.3	39
ITC	ALS+Hyper.	9	1.2	35
SITC	ALS	16	1.8	57
SITC	ALS+CIR	12	1.4	48
SITC	ALS+RGBI	9	1.4	52
SITC	ALS+Hyper.	25	1.9	48

[a] Values in percentage of results obtained using field reference data (NPV=6,069€ha^{-1})

slightly higher RMSE values than in similar studies where more plots were used (Breidenbach et al. 2010).

The results according to the predicted distributions were generally in line with previous studies (Bollandsås and Næsset 2007; Gobakken and Næsset 2005) even if the size of the sample plots was slightly smaller than what is recommended (Gobakken and Næsset 2005). It should be noted that comparing the resulting diameter distributions from the inventory approaches was beyond the scope for the current study.

The ITC results with a detection rate of 45 % were at the same level as could be expected in this forest area. The stem diameter error of 4.6 cm obtained in the current study was slightly higher than those reported in other studies. Persson et al. (2002) found an error of 3.8 cm, and Ørka et al. (2010) found RMSE values of 3.1–3.5 cm. The levels of accuracy that we obtained for species classification using ALS and ITC were equal or slightly smaller than those obtained in other Scandinavian studies (Holmgren et al. 2008; Korpela et al. 2010; Vauhkonen et al. 2010). However, the improved accuracy when adding information from multispectral imagery were more pronounced than what was obtained by e.g. Holmgren et al. (2008). The improvement in the current study was 15–17 percentage points, while Holmgren et al. (2008) reported an improvement of five to eight percentage points. Adding hyperspectral imagery improved the overall accuracy with additional six to nine percentage points and the κappa value by more than 0.11 units. However, the improved accuracy of the tree species classification had only minor impacts on the mean stand level results, and this was mainly related to the large systematic errors caused by the low detection rate.

The results for SITC were similar to what were found by Breidenbach et al. (2010) in the same study area. However, the methodology used in the current study deviated from this publication by imputing tree list information from the segments as required by the decision support system and not only the total values. Furthermore, Breidenbach et al. (2010) only investigated estimation of stem volume in total and distributed on species. It should be noted that the RMSE values for number of stems and tree heights obtained using SITC were the smallest in the current study (Table 4).

4.2 Economic loss

When evaluating the effects of how errors in inventory data affect management decisions and subsequently affect the economic value in the current study, the same approach as in Eid et al. (2004) was followed. However, Eid et al. (2004) used ABA-MV and a stand simulator (Hoen and Eid 1990), while we use a single-tree-based simulator to be able to assess the value of the single tree data and diameter distributions obtained from the different inventory approaches. Both Eid et al. (2004) and the current study applied a 3 % interest rate. Holmström et al. (2003) showed that interest rate may influence results under very different inventory approaches. The interest rate also affects the optimum harvest time. Thus, with a large interest rate, the harvest age will be low and the effect of erroneous data diminishes, and accordingly, the need for accurate data decreases, at least when considering data for old forests.

Our results show that a large loss is avoided if ABA-DD, ITC or SITC are used to acquire the information instead of ABA-MV. The d_g, h_L and N obtained from the ABA-MV did not give a sufficient description as basis for decision-making regarding timing of harvest. The diameter distribution models applied when only mean tree data were used as input to the single tree simulator have been previously evaluated by Eid (2002), who concluded that the models were not able to properly describe the stand structure and should not be used when valuing stands or as a basis for long-term planning and decision-making. Furthermore, as uneven-aged forestry becomes more popular, ABA-MV and the use of stand simulators should be avoided since these are only able to describe the development of the average tree per treatment unit or stand.

Our favourable results for ABA-DD were in line with the findings by Eid et al. (2005). However, the costs of the remote sensing data to aid forest inventories are highly dependent on the size and shape of the inventory area together with the spatial resolution of the data. Remote sensing data are often used for multiple purposes, such as terrain mapping and planning of infrastructure, and data costs are shared between users. Thus, data costs for forest inventory varies. Of the inventory approaches considered in this study, ABA-MV is the least expensive. The cost of ABA-DD is about the same as ABA-MV, but slightly larger sample plots might be required to capture variation since irregular diameter distributions may result from inadequate sample plot sizes (Cao and Burkhart 1984; Gobakken and Næsset 2005). For ITC or SITC, a point density of about five to ten points per square meter are generally needed (Vauhkonen et al. 2012a). The higher point densities required for ITC and SITC increase the ALS costs for these inventory approaches even if the capacity of ALS instruments to provide higher point densities with the same flight plan is increasing by using waveform recording sensors, multiple pulses in the air or similar approaches. Thus, the cost of ALS data for ITC and SITC inventories is about three times higher than the data for an ABA inventory in Norway. According to our knowledge, SITC has so far not been applied in operational inventories. Due to the need for a number of georeferenced single trees, costs are expected to be larger than for ITC. However, methods for combining high- and low-density airborne laser scanning data have been developed and tested (Breidenbach et al. 2012), and the value of the resulting inventory data should be evaluated in future studies.

Spectral images might be acquired during the same flight as ALS data (as CIR in the current study), but simultaneous acquisitions put restrictions on the available time for flights with ALS instruments; acquisition at night time would, for example, not be feasible. Thus, costs will increase due to both acquisition and data processing when spectral data are needed for the forest inventory. Hyperspectral data have not been used for operational forest inventories in the Nordic countries and due to increased data complexity, both acquisition and processing costs are expected to be larger than for multispectral data. However, recently, the use of hyperspectral imagery has been shown to be highly beneficial when estimating species composition in boreal forest both using ABA (Ørka et al. 2013) and ITC (Dalponte et al. 2013). Moreover, the use of ITC has benefits when it comes to estimation of the minority species (Ørka et al. 2013).

The fact that we considered only one management decision, i.e. final harvest, clearly limits the generality of our results. There is a trade-off between simplicity in simulations and generality in answers, and we opted for simplicity in simulations in our case study. This choice is also closely related to the small data set in this study. However, the harvest decision is maybe the most important management decision in commercial forestry, and the results are hence of interest even from a small case study. We consider the field measurements as field reference values free of errors. This is obviously a simplification as the data may contain measurement errors, both random and systematic, as well as model errors in volume models and other standard models used. Furthermore, we have only considered errors in tree level information. Certain stand level variables are also important for management decisions, amongst them stand age and site index. For example, Eid (2000) shows how site index is important for scheduling the final harvest. The variables stand age and site index may not be obtained from remote sensing based inventories, although there have been attempts to derive site index from ALS data (Vehmas et al. 2011). Furthermore, the use of uncertain inventory data, e.g. uncertainty in tree height derivation from ALS, in forestry scenario models leading to propagation errors and consequential incorrect harvest decisions and uncertainty in NPV is outside the scope of this study.

5 Conclusions

When the costs of the inventories are also taken into consideration, ABA-DD using ALS as the only remote sensing data source appears to be an approach providing a favourable combination of accuracy and costs. Adding a diameter distribution to the standard area-based approach, i.e. going from ABA-MV to ABA-DD, does not exclude the option to use mean values where such information is better suited. We are confident when we conclude that the added complexity and detailed information from using auxiliary data sources has no clear positive effect on the value of the inventory following the approaches presented, i.e. the cost/benefit-ratio is high. The reason for this lack of positive effect is that the increased accuracy of the tree species information obtained with spectral information is not large enough to alter the decision of when to harvest. No effort has been made in the present work to search for an optimum with respect to inventory approach where accuracy and costs are balanced for the amount of field data, ALS settings such as point density etc. The results are based on a small number of stands, located in a municipality in south-eastern Norway, with a limited variation in species composition. Still, the results should provide an appropriate illustration and at least an indication of the relative relationship between the evaluated inventory approaches under similar forest conditions. Further studies are needed to verify our results and evaluate their relevance to other forest conditions.

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