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Airborne laser scanning based forest inventory for forest management by applying novel metrics and multiple data sources

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Academic dissertation

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ABSTRACT

The aim of this work was to develop airborne laser scanning (ALS) based forest inventory for practical forest management by applying novel horizontal metrics and multiple data sources. In particular, this work examined classification of forest land attributes (study I), prediction of species-specific stand attributes (study II) and detection of spatial pattern of trees (study III) and need for silvicultural operations, such as first thinning (study III) and tending of seedling stand (study IV). An area-based approach was used together with different classification or prediction methods in all studies. Multiple data sources were used to calculate a combination of predictor variables: in study I ALS data and satellite images, in study II ALS data, aerial images and stand register data, and in study IV ALS data and aerial images. The applicability of horizontal ALS-based metrics was tested in studies I and III. In study I the applicability of field data from national forest inventory of Finland as a training data was also tested. The classification of land use/land cover classes was highly accurate. Also, classification of site fertility type, peatland type and drainage status succeeded moderately well. The prediction of species-specific stand attributes of several tree species was more accurate when tree species proportions from existing stand register data were used in prediction. The classification accuracies were very high for the spatial pattern of trees and need for first thinning, and moderately high for the need for tending of seedling stands. Horizontal ALS-based metrics were the most applicable predictor variables in classification of land use/land cover, main land type, drainage status, detection of spatial pattern of trees and need for first thinning. To conclude, this work provided valuable methodological know-how on the applicability of novel horizontal ALS-based metrics and the use of multiple data sources for cost-effective forest inventory and planning. Some of the methods have already been implemented in practical forest inventories in Finland.

Keywords: ALS; Forest inventory; Forest management; Horizontal metrics, Multiple data source; Silvicultural need

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Last sentence is for you Jonas “I give you all of me, you give me all of you” kiitos <3

Joensuu, May 2015

Inka Pippuri

LIST OF ORIGINAL ARTICLES

This thesis is based on following articles which are referred in text by their Roman numerals:

I Pippuri I., Suvanto A., Maltamo M., Korhonen K.T., Pitkänen J., Packalen P. Classification forest land attributes using multi-source remote sensing data. Submitted manuscript.

II Pippuri I., Maltamo M., Packalen P., Mäkitalo J. (2013). Predicting species-specific basal areas in urban forests using airborne laser scanning and existing stand register data. European Journal of Forest Research 132 (5-6): 999-1012. http://dx.doi.org/10.1007/s10342-013-0736-8

III Pippuri I., Kallio E., Maltamo M., Peltola H., Packalén P. (2012). Exploring horizontal area-based metrics to discriminate the spatial pattern of trees and need for first thinning using airborne laser scanning. Forestry 85(2): 305-314. http://dx.doi.org/10.1093/forestry/cps005

IV Korhonen L., Pippuri I., Packalén P., Heikkinen V., Maltamo M., Heikkilä J. (2013). Detection of the need for seedling stands tending using high-resolution remote sensing data. Silva Fennica 47(2). http://www.silvafennica.fi/pdf/article952.pdf

The articles II, III and IV are reprinted with the kind permission of publishers, while the article I is the author version of the submitted manuscript.

Inka Pippuri is the main author of articles I, II and III. In study I she was responsible for most of the analysis and calculations, except for the part of the laser data processing and stages involving analyses of satellite images. Similarly, she was responsible for most of the work in studies II and III, except for the creation of grid-cells and modelling using nearest neighbor method (II), processing of ALS data and writing code for calculation of landscape metrics (III). In study IV she participated in the processing of ALS data, modelling using logistic regression, calculating results and writing the article. She also participated in collecting field data in studies II and III. All the articles were improved based on comments by co-authors.

TABLE OF CONTENTS

ABBREVIATIONS

ABA	Area-based approach
AI	Aerial images
ALS	Airborne laser scanning
CHM	Canopy height model
CV	Cross-validation
DBH	Diameter at breast height
DGPS	Differential global positioning system
DSM	Digital surface model
DTM	Digital terrain model
FAO	Food and agricultural organization of the United Nations
GPS	global positioning system
ITD	Individual tree detection
LDA	Linear discriminant analysis
LogR	Logistic regression
LR	Linear regression
LU/LC	Land use/land cover
MlogR	Multinomial logistic regression
NFI	National forest inventory
NIR	Near-infrared
NN	Nearest neighbor method
OA	Overall accuracy
R^2	R squared, coefficient of determination
RMSE	Root mean square error
RS	Remote sensing
SI	Satellite images
SVM	Support vector machine
TSP	Tree species proportions

1 INTRODUCTION

1.1 Practical ALS-based forest inventory in Finland

In practical forestry, accurate information about growing stock and stand characteristics are crucial for successful forest management and planning. In Finland this information was earlier collected using a stand-wise field inventory method based on placing of angle count sample plots and partly visual assessment (Koivuniemi and Korhonen 2006). During the 2010s, that method has been replaced with a new inventory system using a combination of airborne laser scanning (ALS) data, aerial images (AI) and field measurements (Maltamo and Packalen 2014). Compared to the traditional field inventory, based on the new ALS-based inventory system, stand attributes can be determined for large areas objectively, accurately and in a cost-efficient way (e.g. Næsset 2002; Næsset et al. 2004; Jensen et al. 2006; Packalén and Maltamo 2007).

ALS is an active remote sensing (RS) technology (Wehr and Lohr 1999), producing a three-dimensional description of forest canopy, which has made it an important technique for forest inventories. Different ALS-based metrics are calculated from the ALS data to predict characteristics of a target. The inventory methods can be divided into two different kinds of approaches depending on the inventory unit. In an area-based approach (ABA) (Magnussen and Boudewyn 1998; Næsset 2002), which usually uses low pulse density ALS data, the inventory unit is usually a plot, a microstand or a stand. Another approach used to produce forest information is individual tree detection (ITD), which uses high density pulse data (e.g. Hyyppä and Inkinen 1999; Popescu et al. 2003). Both approaches can also use spectral data as additional information.

Several studies have shown that ABA provides reliable and unbiased estimates of growing stock, and nowadays, it is the main approach in practical forest inventories (Næsset et al. 2004; Maltamo and Packalen 2014). For example, in Finland ABA has provided more accurate results for total attributes of growing stock compared to earlier field inventory (Suvanto et al. 2005). Also, accuracies of species-specific attributes are partly comparable with the old inventory method. The accuracy of tree and stand attributes based on ITD has also been relatively good. But difficulties in tree detection and prediction of diameter together with higher data acquisition costs have limited the operational use of ITD.

In the ABA, the prediction of forest attributes is based on the statistical relationship between forest variables measured in the field and predictor features derived from the ALS data (Magnussen and Boudewyn 1998; Næsset 2002). Also, spectral RS data or other existing information can be utilised as additional information. RS features are extracted from the same area where forest variables are measured, e.g. plot. In this approach, first statistical dependency between forest variables and RS features are modelled, and then forest variables are predicted for the area of interest, e.g. grid-cell, using this dependency. Metrics calculated from the height, density and intensity distribution of ALS point cloud are the most often used as predictor variables in the ABA studies (Næsset et al. 2004; Vauhkonen et al. 2014A). Additionally, some horizontal metrics calculated from ALS-based surfaces like the digital terrain model (DTM) or canopy height model (CHM) have been tested (Van Aardt et al. 2008; Korpela et al. 2009; Korhonen et al. 2011; Vastaranta et al. 2012; Racine et al. 2014). Other information used together with the ALS metrics can be, for example, spectral and texture metrics, which are calculated from AI or satellite images

(SI) (e.g. Packalén and Maltamo 2007) or information from existing stand register data (e.g. Maltamo et al. 2006; Närhi et al. 2008).

Estimation methods can be divided into parametric regression methods and non-parametric nearest neighbor (NN) methods (Vauhkonen et al. 2014A). Prediction unit in ABA is usually a circular plot, grid-cell, microstand or a stand. Microstand is a homogeneous forest stand, usually smaller in size than a normal stand (Hyvönen et al. 2005). The size of the prediction unit depends on the purpose of inventory, and it usually corresponds to the size used in training data. Wall-to-wall prediction for large areas is usually done using a grid approach.

The new ALS-based inventory system in Finland uses a combination of low density ALS data, AI, field measurements and the ABA as the prediction method. Accurately geo-referenced field sample plots (usually 9 m radius circular plot) should represent the whole variation of inventory area including different developing stages of forest and tree species. For example, in the inventory area of 1000–5000 km^2, about 500–700 plots are placed into young, maturing and mature forests and 100–150 in seedling stands, but very often small seedling stands (height < 1.3 m) are left out from sampling. Both leaf-on and leaf-off data are used, but they cannot be mixed in the same project, except if both datasets cover wall-to-wall same inventory area (Villikka et al. 2012). Leaf-on data is collected in the summer, when deciduous trees are in leaf. In the ideal case, ALS data, AI and field data are collected in the same year, but often there is a time difference of one year between acquisitions (Maltamo and Packalen 2014).

Species-specific stand attributes are predicted based on metrics calculated from ALS point cloud data and AI (Packalén and Maltamo 2006, 2007, 2008). The spectral and textural metrics from AI are used to improve the separation between tree species. In the NN imputation, the species-specific stand attributes and sum attributes are predicted simultaneously, which guarantees more logical results. Also, prediction of species-specific diameter-distributions is possible using NN (Packalén and Maltamo 2008). Stand attributes are predicted wall-to-wall in a whole inventory area using the grid-cells size of 16 x 16 m, which approximately corresponds to the size of field plots. The mean values of grid-cells within each stand are calculated to obtain the stand level results. The CHM is used parallel with the orthorectified AI in manual stand delineation. However, semi-automated stand delineation by means of segmentation is also established as part of the inventory. Segmentation is usually used to create homogeneous microstands from which final stands are composed for operational use (Maltamo and Packalen 2014). In Finland, most actors of practical forestry have updated their inventory and planning systems to support the new ALS-based inventory method. Nowadays, this inventory system is applied for almost 3,000,000 ha annually.

1.2 Predicting forest land and stand attributes

Despite the cost-effectiveness and estimation accuracy of growing stock attributes, the ALS-based inventory system has not yet fulfilled all the expectations and needs of practical forest management. In this respect, the application of novel horizontal ALS-based metrics together with multiple data sources could offer new possibilities to predict in an accurate and cost-efficient way the forest land and species-specific stand attributes, and to detect the spatial pattern of trees and need for silvicultural operations.

Estimating forest land attributes. Forest land and site type classifications are used both at the national and international level to monitor the amount, properties and state of forests. In forestry, different classifications of forest land attributes, like main type, site fertility type, peatland type or drainage status are also important, as they form the basis for prediction of forest growth and silvicultural operations. In Finland, forest land and site fertility type information is collected in the National Forest Inventories (NFI) and in the regional stand-wise forest inventories supporting forest planning. In practice, most of the forest land attributes are collected from existing stand register data, not estimated based on ALS data.

There are several studies where forest land and different forest types have been discriminated using ALS and other RS data, but classification of different forest land attributes has gotten much less attention. In some land use studies, wetlands and peatland (swamp) forests have been mapped using RS with varying results (e.g. Maxa and Bolstad 2009; Sader et al. 1995; Townsend and Walsh 2001). In study of Maxa and Bolstad (2009) use of lidar data (DTM) together with satellite images improved the wetland/upland distinction. So far, in the ALS-based studies, mineral soils and peatlands or different drainage status of forests have not been separated from each other. However, recently Dirksen (2013) discriminated peatland (swamp) forests and upland forests (non-paludified, mineral soil) using ALS point cloud metrics with accuracy of 54-62%. Dirksen's study showed that vegetation in peatland forests was lower than in upland forests.

Site classification in Finland uses Cajander's (1926) forest site fertility type theory, which is based on understory vegetation. Even though the stand attributes (volume, basal area, mean height and mean diameter of growing stock) can be predicted with a high accuracy in the ALS-based forest inventory, classification of site fertility types has only been tested in a few studies. Vehmas et al. (2011) classified forest site fertility types in mature forests on mineral soils using ALS point cloud metrics with kappa-value of 0.47. Korpela et al. (2009) tested ALS point cloud and surface (DTM) metrics in the classification of mire habitats, being able to classify 21 mire types with a kappa of 0.25–0.62. Corresponding kappa-values for the main mire types (treeless, composite and forested) were 0.32–0.67 and for dominant tree species (spruce, pine and spruce-pine) 0.66–0.81, respectively. Recently, the potential of ALS point cloud metrics to identify herb-rich forests has also been studied (Vehmas et al. 2009). Overall accuracy (OA) was 89 % and herb-rich forests were classified correct in 65 % of cases.

Worldwide, a more common method for site classification is a site index, which is based on the dominant height of growing stock at a certain age. For instance, Gatziolis (2007) estimated the dominant height and site index using ITD, and Packalén et al. (2011) did it using ABA. Holopainen et al. (2010) used dominant height predicted from the ALS data and the stand age from stand register data to determine the site indices and then converting them into site types. They found a kappa-value of 0.60 for five site fertility types.

Prediction of forest land attributes using ALS-based inventory has been studied only little and results of the site type classifications are not yet in a sufficient level. Hence, RS based prediction of forest land attributes such as separation of mineral soils and peatlands, classification of forest site fertility type, peatland type or forest drainage status needs more careful examination. In this respect, the application of new horizontal ALS-based metrics calculated from different ALS-based surfaces and combined used of multiple data sources like ALS data, SI and field plots from NFI could enable more accurate and cost-efficient classification of forest land attributes.

Estimating species-specific stand attributes. In forest management and planning, tree species information is needed for determining species-dependent forest treatments and for predicting species-specific growth and yield. So far, in the Finnish ALS-based forest inventory system, only Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) Karst) and deciduous tree species as one stratum have been considered. This is because these conifers represent together about 80% of the total growing stock, and the remainder comprises deciduous tree species (mainly *Betula* spp.) (Finnish Statistical Yearbook of Forestry 2014). In general, it is also extremely difficult to discriminate deciduous species by using metrics of AI and ALS data.

The ABA, which uses the NN method to predict species-specific stand attributes, has been mainly developed by Packalén and Maltamo (2006, 2007, 2008). In this approach, point cloud metrics from ALS data, and spectral and textural metrics from AI are used as predictor variables. The main tree species is usually predicted correctly but the error on minor tree species is very high. In the study of Packalén and Maltamo (2007), accuracies for species-specific volume at stand level were 28, 33 and 62% for Scots pine, Norway spruce and deciduous species. Wallenius et al. (2012) found similar values for pine and deciduous trees in microstand level, but root mean square error (RMSE) of spruce was a bit higher. Packalén et al. (2009) slightly improved the prediction accuracy by linking ALS points to the pixel values of unrectified AI. Similarly, Maltamo et al. (2014) pre-classified data according to the main tree species and stand development stages. Niska et al. (2010) suggested neural networks as an alternative estimation method for NN, respectively. Recently Villikka et al. (2012) found leaf-off data to provide more accurate estimates than leaf-on data and discriminated between coniferous and deciduous trees even without the use of AI. Vauhkonen et al. (2012, 2013) found alphashape metrics and intensity distribution promising in tree species separation, respectively.

In the management of urban forests, information on different tree species, including deciduous tree species (such as *Quercus robur*, *Tilia cordata*, *Populus tremula*, *Alnus glutinosa, Betula pubescens* and *petula Pendula*) and their proportions are needed in greater detail compared to the management of commercial forests. This is because in urban forests, the main focus is on landscape value, maintenance of biodiversity and providing protection from noise, wind and pollution instead of timber production (e.g. Robinette 1972; Miller 1997). Despite this, the inventory system of urban forests has not yet considered different deciduous species in detail.

There is some evidence that the ABA could separate different deciduous tree species, such as *Fagus sylvatica* and *Acer speudoplatanus* **(**Breidenbach et al. 2010A) or *Betula* spp. and *P. tremula* (Breidenbach et al. 2010B). In the study of Breidenbach et al. (2010A), the relative RMSE of species-specific plot volumes varied from 80 to 315% for *Fagus sylvatica, P. abies, Abies alba, Pseudotsuga menziesii* and *Acer speudoplatanus*. They also tested species-related variables from the inventory by compartments (e.g. forest type, age class), but only ALS-based predictor variables were selected in final models. In temperate and urban forests, ALS-based studies on several tree species have focused on tree species classification, not prediction of the species-specific stand attributes (e.g. Vauhkonen et al. 2014B).

Current ALS based inventory system cannot produce species-specific information with desired accuracy, despite several improvement attempts in research. One option to improve the prediction of species-specific stand attributes, especially in forests with several tree species in urban forests, could be the combined use of ALS data and existing stand register data. The species proportions with respect to basal area (or number of stems) can be regarded as the most reliable data in stand registers, because angle-count sampling used an old inventory system in Finland. The use of ALS data in conjunction with stand register and field data could also be an economically beneficial and viable solution.

Estimating spatial pattern of trees. The spatial pattern of trees in a forest can be defined as the locations of the trees in relation to each other. It can be regular, random, clustered, or any combination of them (e.g. Pielou 1960; Tomppo 1986). The spatial pattern of trees, based on tree locations in a two-dimensional space, can be estimated statistically using dedicated sampling designs or by measuring the exact locations of all trees. The scale used in the analysis also affects this classification. Spatial pattern has been proved to have a significant effect on tree growth, but because fieldwork for measuring the spatial pattern of trees is rather laborious and expensive, it has not been widely utilised in forestry applications, including prediction of growth and yield for forest planning (e.g. Kilkki et al. 1985; Gavrikov and Stoyan 1995; Pukkala et al. 1998). In practical forestry, the spatial pattern of trees has been taken into account when determining the need for silvicultural operations like the need for tending of seedling stand or thinning. But, in such cases, spatial properties are evaluated visually, never measured or quantified.

According to Coops and Culvenor (2000), it would be possible to estimate the spatial pattern of trees in a stand using local variance of simulated high spatial resolution imagery, if crown size is provided a priori. Spatial pattern of trees have also been estimated by segmenting single trees and calculating landscape metrics from AI (Uuttera et al. 1998). However, according to Uuttera et al. (1998), this approach was not viable because clustered spatial pattern were often misclassified as regular pattern, and regular pattern as random pattern. The most obvious way to use ALS data in the determination of the spatial pattern of trees would probably be ITD, where the positions of trees can be located (e.g. Mustonen 2002). Packalen et al. (2013) tested ITD, semi-ITD and ABA for determining spatial pattern of trees with low results. In both ALS-based studies (Mustonen 2002; Packalen et al. 2013) it was found difficult to detect clustered spatial pattern of trees. The use of new horizontal ALS-based metrics, such as texture or landscape metrics, could be expected to offer possibilities for accurate and cost-effective classification of spatial pattern of trees in ALS-based forest inventory.

1.3 Determining need for silvicultural operations

Determining the need and timing for silvicultural operations, especially the need for tending of seedling stand and first thinning, has a great impact on the growth and dynamics of stands as well as amount and profitability of timber production over a rotation. In Finland, the determination of need for silvicultural operations is still partly done based on a stand-wise field assessment. Determining the need for silvicultural operations is not explicit, for example, the need for the tending of seedling stands is usually evaluated based on stand density (trees per hectare), spatial pattern of trees, species proportions, height difference of deciduous and conifer trees, quality of seedlings and site fertility type. In the practical ALS-based forest inventory system, the need for silvicultural operations can be determined by means of estimated stand attributes or through additional fieldwork.

Several studies have examined the possibility of determining the need for silvicultural operations using the ALS data. For example, Kotamaa et al. (2010) defined the need for silvicultural operations based on stand-level tree diameter distributions derived from the ALS data with OA of 75% and kappa-value of 0.61. Nivala (2012) predicted need for fuel wood thinning and tending of seedling stands in young and seedling stands using point cloud metrics. His kappa-value using three classes was 0.65 and OA of 100 % for fuel wood thinning and 79 % for tending of seedling stands. Vastaranta et al. (2011) used ALS metrics to predict the thinning maturity with OA of 79% for stands with thinning need for 10 years and 83% for stand with immediate thinning need. Halvarsson (2008) predicted a forest density index, which was linked to the thinning need (with R^2 of 0.9). Predicting seedling stand attributes, especially density, (Næsset and Bjerkness 2001; Närhi et al. 2008) or detection of the need for tending of seedling stand (Närhi et al. 2008; Tahvanainen 2011; Nivala 2012) has been found more difficult to assess accurately. For example, Närhi et al.

(2008) and Tahvanainen (2011) classified the need for tending of seedling stand with kappa-values of 0.54 and 0.58. In study of Närhi et al. (2008), Tahvanainen (2011), Vastaranta et al. (2011) and Nivala (2012) direct prediction of need for silvicultural operation was found to be even better alternative than the prediction of stand attributes followed by the decision of silvicultural operation needs. Also use of existing stand register data has been tested in couple studies, but only in study of Närhi et al. (2008) existing information about stand age was utilized in prediction of seedling stand density. Low prediction accuracy of seedling stand attributes in earlier studies is one reason why seedling stands are still mostly field-checked. Another reason is that every 10 years repeated ALS-based inventory is too rare for successful management of seedling stands with a high growth rate.

The efficiency of forest inventory system could be enhanced if accurate determination of the need for silvicultural operations could be obtained in an ALS-based forest inventory. In this respect, the use of new horizontal ALS-based metrics, multiple data sources and direct prediction of tending or thinning need without predicting other stand attributes could improve the detection of need for silvicultural operations.

1.4 Objectives

The overall aim of this work was to develop ALS-based forest inventory for practical forest management by applying novel horizontal metrics and multiple data sources. In particular, this work examined the classification of forest land attributes (study I), prediction of species-specific stand attributes (study II), detection of spatial pattern of trees (study III), and the need for silvicultural operations, such as first thinning (study III) and tending of seedling stand (study IV). The specific objectives of the individual studies were:

I to examine the success of classification of forest land attributes using ALS data, satellite images and sample plots from NFI as training data and to test applicability of horizontal ALS-based surface metrics in the classification of forest land attributes,

II to examine the success of prediction of species-specific stand attributes using a combination of ALS and existing stand register data in urban forests,

III to identify point cloud metrics and horizontal texture and landscape metrics for determination of spatial pattern of trees and need for first thinning, and to study if clustered spatial pattern of trees and the need for first thinning can be separated from other spatial pattern and the need for thinning classes, and

IV to evaluate the applicability of high resolution remote sensing data in seedling stand inventory and test direct classification of seedling stands into tending need classes without predicting other stand attributes.

2 MATERIALS

2.1 Study areas and field data

Study areas. Experimental work was carried out in four different study areas (Figure 1). Forests in Päijät-Häme (study I), Janakkala (study III) and Joutsa (study IV) can be considered as typically managed boreal forests dominated by Norway spruce and Scots pine. The study area in Päijät-Häme also included agricultural lands, water (lakes) and built areas. The Turku study area (study II) belongs to the hemiboreal vegetation zone, where hardwoods occur abundantly and mixed forests of coniferous and deciduous trees are more common than in typical managed boreal forests. The Turku study area consisted also forests both in urban areas and the countryside. A summary of data used in different studies I-IV is shown in Table 1.

Field data. In study I, field data of 828 plots were collected in 10^{th} and 11^{th} NFI during 2008-2012. The centres of sample plots were located in the field using raw GPS (global positioning system) positions according to instructions of NFI of Finland (VMI11 maasto-ohje 2009). In this study, plots that had only one forest stand or national land use/land cover (LU/LC) class within the 12.52 m radius were utilised. The following classifications determined for each plot were used: national and FAO LU/LC class, main type, site (fertility) type, peatland type and drainage status. Classifications are determined for the forest stand, or the parcel of land use class, in which the centre point of the plot is located. In the final classification, national LU/LC class included following classes: forestry land, agricultural land and class built. FAO LU/LC classes were forest and non-forest. The main type consisted of mineral soil and peatland. Forest site type classes were very-rich, rich, medium, poor and very poor. Site types were also classified into three classes when very-rich and rich were combined as well as classes poor and very poor. Each site type class indicated the site fertility of mineral soils or the corresponding peatlands. Peatland classes considered were spruce peatland, pine peatland and open peatland, respectively. Drainage status was divided into classes undrained and drained.

In study II, 205 circular plots were measured in summer 2010 from stands with different developing stages and dominant tree species. Differential global positioning system (DGPS) was used to determine the position of the centre of each plot. The diameter at breast height (DBH) and tree species was measured from each tree with DBH greater than 5 cm inside the 9 m radius plot. Tree species were divided into seven (*P. sylvestris, P. abies, Betula sp., Q. robur, P. tremula, A. glutinosa* and other deciduous trees) and three (*P. sylvestris, P. abies* and deciduous trees) species strata. These species were selected because they were the most dominant tree species in the stand register data. The basal area by tree species and total basal area were calculated for each plot. Validation data of 52 forests stands (size 0.5-2 ha) were measured in summer 2012, including stands dominated by pine, spruce, hardwoods and other deciduous trees. In this thesis hardwood species include *Q. robur, T. cordata, Fraxinus excelsior, A. platanoides* and *Ulmus spp*. Species-specific basal areas were calculated based on fifteen angle count sample plots systematically placed for each stand. Tree species proportions (TSP) from existing stand register data were utilised using same tree species strata (seven and three) as in training and validation data. Existing stand register data was collected from 1990 to 2002 and updated to June 2010 using growth models (Hynynen et al. 2002).

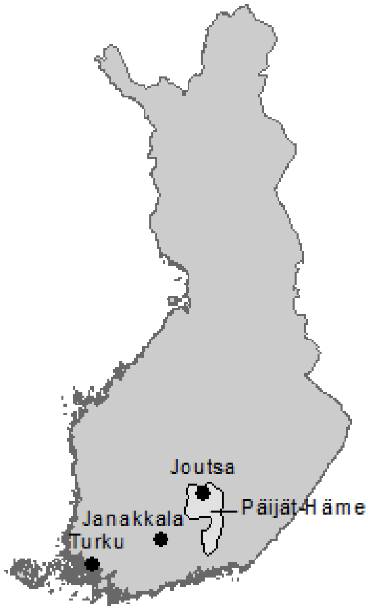

Figure 1. Location of study areas.

Table 1. Summary of data used in different studies (I-IV), including ALS data properties. N = number of, RS = remote sensing data. ALS = airborne laser scanning, AI = aerial images, SI = satellite images, CV = cross-validated reference data.

Study	I	II	III	IV
Location	Päijät-Häme	Turku	Janakkala	Joutsa
N plots/segments	77-828	205	28	208
RS data	ALS, SI	ALS, AI	ALS	ALS, AI
Validation data	CV	52 stands	CV	68 stands
ALS data				
Instrument	Opetech ALTM 04 sen 161	Leica ALS50-II	Optech ALTM3100	Optech ALTM Gemini
Acq. time	Summer 2010	Spring 2009	Summer 2007	Summer 2010
Pulse density	0.54	1.56	0.62	0.54
Flying height	2000	1200	2400	2000
Scan angle	30	40	30	30

In study III, the field data consisted of 28 microstands measured in summer 2009. Microstands reached the first thinning phase but had not yet thinned and they were dominated by Scots pine or Norway spruce. *T*-square sampling, which is based on point-to-point distance measurements, was carried out in each microstand, offering efficient and statistically coherent measurements to define spatial patterns of vegetation (see e.g. Besag and Cleaves 1973). Classes of the spatial pattern of trees for the microstands were defined with spatial indices (Diggle 1983). The *tN*-index of Besag and Cleaves (1973) appeared to be the most suitable for the *T*-square measurements and also *M*-index (Bartlett 1937) were used. The need for first thinning was defined on the basis of basal area measurements, dominant height and visual assessment of the tree characteristics following the Finnish forest management recommendations (Hyvän metsänhoidon suositukset 2006). Determination of the spatial pattern of trees resulted in 11 clustered and 17 random/regular microstands, and the need for first thinning was performed on 15 microstands.

In study IV, the field data consisted of 208 seedling stand plots (height between 1.3 and 9 m) with different height, density and dominant tree species. DGPS was used to determine the position of the centre of each plot. Stem density (number of trees) and median tree characteristics by tree species were measured from each plot with 9 m radius in summer 2010, and the need for tending was evaluated in autumn 2010 or spring 2011. Final training data included 103 plots with need for tending, and 105 plots without need during the next 5 years. Validation data was collected from the same area in autumn 2011 and included 45 seedling stands with a need for tending and 23 without. The need for tending was evaluated visually, and stem density (number of trees) was assessed using subjectively located 50 m^2 circular plots inside stands. Despite following Finnish management recommendations, the evaluation of timing for need of tending was still very subjective and depended on the local conditions. It was evaluated by experienced local foresters.

2.2 Remote sensing data

Leaf-on ALS data was used in studies I, III and IV and leaf-off data in study II. Laser scanning systems used in all studies captures four range measurements for each pulse, but the measurements were reclassified to represent first and last pulse echoes in studies II, III and IV and first, last and intermediate echoes in study I. The first echo data contained the echo categories ‘first of many’ and ‘only’, while the last echo data contained ‘last of many’ and ‘only’ echoes. Main properties of ALS datasets are shown in Table 1. DTM was generated from the ALS data. First, the laser points were classified to ground points and other points (method explained by Axelsson 2000) and then a DTM raster was created from the ground points by taking the mean height of the points within each raster cell. The orthometric heights of laser hits (z value) were converted to above ground heights by subtracting the DTM at the corresponding location. Only in study IV were raw echo intensities normalised for range (Korpela et al. 2010). In studies I and III, the CHM was generated from first echo data by taking the maximum height at above-ground scale within a certain radius from the centre of a pixel. In study I, a digital surface model (DSM) was also generated by summing up the pixel values of DTM and CHM rasters. The pixel size of surface models (DTM, DSM, CHM) was one or two metres depending on the study.

Aerial images (AI) were taken in June (study II) and July (study IV) 2010 using Vexcel UltraCamD digital aerial camera. In study II, flying altitude was 2512 m, sidelap 30% and endlap 50%. The same values for study IV were 2700 m, 30 and 80%. In study II, pan-sharpared green, blue and near-infrared (NIR) bands and in study IV, original red, green, blue and NIR bands and pan-sharpared NIR band were used. Pan-sharpened images were orthorectified to a 15 cm (study II) and 25 cm (study IV) resolution. In study I, satellite data consisted of two Landsat 5 TM images acquired June and July 2010. Spatial resolution of images was 30 metres. The Landsat 5 TM imagery had seven bands: blue, green, red, NIR, shortwave infrared, thermal infrared and reflective infrared.

3 METHODS

3.1 Inventory units, estimation methods and accuracy assessment

In this work, ABA was utilised in all studies with the following modelling units: circular plot (studies I, II, IV), segment (study I) and microstand (study III). The segments were created by generating a 50-metre buffer around the plot centre and delineating a homogeneous segment within the buffer zone (see Fig. 3 in study I). It was assumed that the larger segment better represents the forest stand or land use area compared to a small circular plot. CHM was used in manual delineation of homogeneous segments around a plot. Microstand-level inventory was chosen for study III since the size of the microstands was most suitable for field measurements and it resulted in inventory units that were sufficiently homogeneous in their forest characteristics. Homogeneous microstands were formed using a method presented by Leppänen et al. (2008). In studies II and IV, separate validation data was also used. Prediction was done into 16 m x 16 m grid-cells and stand level results computed as mean value of grid-cells inside stand borders (see Fig. 3, in studies II and IV).

Multinomial logistic regression (MlogR, e.g. Greene 2002) was used to classify forest land attributes in study I and linear discriminant analysis (LDA, e.g. Venables and Ripley 2002) to classify spatial pattern of trees and the need for first thinning in study III. In study IV, linear regression (LR) was used to model the stem density, and both logistic regression (LogR) and support vector machine (SVM, Schölkopf and Smola 2002) to classify need for the tending of seedling stand. In studies III and IV leave-one-out, and in study I, leave-one-cluster out-cross-validation was used. The summary of studied classification attributes in studies I, III and IV is shown in table 2.

Table 2. Summary of studied classification attributes in studies I, III and IV. N=number of classes.

Classification	N	Classes
Study I		
National LU/LC	2	forestry, agricultural, built
FAO LU/LC	2	forest, non-forest
Main type	2	mineral soil, peatland
Site type 5	5	very rich, rich, medium, poor, very poor
Site type 3	3	rich, medium, poor
Peatland type	2	pine peatland, spruce peatland, open peatland
Drainage status	2	drained, undrained
Study III		
Spatial pattern of trees	2	clustered, regular/random
Need for first thinning	2	need, no need
Combined	4	clustered + need, clustered + no need, regular/random + need, regular/random + no need
Study IV		
Need for tending	2	need, no need within 5 years

Table 3. Summary of estimation methods used within studies. LDA = linear discriminant analysis, LR = linear regression, LogR = logistic regression, SVM = support vector machine, MlogR = multinomial logistic regression, NN = nearest neighbour method, TSP = tree species proportions from stand register data, N pred. = number of predictor variables in models, kappa = kappa-value, OA = overall accuracy, RMSE = root mean square error.

Study	I	II	III	IV
Method	MlogR	LR, NN	LDA	LR, LogR, SVM
Y-variables	national LU/LC, FAO LU/LC, main type, site type, peatland type, drainage status	species-specific basal area	spatial pattern of trees, need for first thinning	stem density, need for seedling stand tending
X-variables	point cloud, surface, texture and spectral metrics	point cloud, spectral and texture metrics, TSP	point cloud, texture and landscape metrics	point cloud, texture and spectral metrics
N pred.	3	3,10	3	3,3,7
Accuracy assessment	kappa, OA	RMSE, bias, kappa, OA	kappa, OA	RMSE, R^2, kappa, OA

In study II, two prediction methods were applied: (1) LR, in which the predicted total basal area was divided into tree species based on TSP from stand register data, and (2) the NN (Moeur and Stage 1995), in which metrics from ALS data and AI and TSP from existing stand register data were used as predictor variables for species-specific basal areas. To compare different data sources, the NN prediction was carried out using the following data combination: ALS data and stand register data (point cloud metrics and TSP from stand register data), ALS data and AI (point cloud metrics and spectral and texture metrics) and all three combined.

Many different predictor variables from different variable groups were tested in each study. Using most of the estimation models, the maximum number of predictor variables was fixed to avoid overfitting or because of data properties. Therefore, all studies considered variable reduction and selection of best metrics, which are more detailed and explained in each study. In studies I and III, the maximum number of predictors was three. In study II, three predictor variables were used in LR for total basal area and ten variables in NN models. In Study IV, three (LogR) and seven (SVM) predictors were selected into best models.

The accuracies of classifications were evaluated based on kappa-value (kappa, Landis and Koch 1977) and OA (See equations 5 and 6 in study III). RMSE and bias (See equations 5 and 6 in study II) were used to evaluate the accuracy of species-specific basal areas in study II and RMSE and R^2 the accuracy and fitness of stem density model in study IV. The summary of estimation methods, variables and accuracy assessment methods is shown in Table 3.

3.2 Predictor variables

In this work, different predictor variables from different data sources were tested. Selected metrics or a combination of metrics were expected to describe the target class or forest attribute. The correlation between forest attributes and metrics calculated from height distribution of ALS points has been shown in several studies (e.g. Næsset et al. 2004; Maltamo et al. 2014). In this work, all metrics directly calculated from ALS point cloud data are called point cloud metrics. Point cloud metrics can be further divided, for example, into height, density and intensity metrics. In this work, they were calculated separately from first and last echo data. Height and density metrics are used to describe the height and density structure of the canopy or target, while intensity metrics describe the mean and variation of the magnitude. In studies I, II and IV, height, density and intensity metrics and in study III, mainly density metrics were utilised. Echo proportions (also intermediate echoes) and some structural metrics calculated using FUSION (McGaughey 2012) were also tested in study I. Calculation methods of point cloud metrics varied slightly between studies.

One aim of this work was to test rarely used horizontal ALS-based metrics. Horizontal ALS-based metrics are calculated from ALS-based surfaces like DTM, DSM or CHM and mainly used in terrain, landscape, hydrological and vegetation density analysis (e.g. Heideman et al. 2012). ALS-based surface (study I), landscape (study III) and texture metrics (studies I and III) are considered as horizontal ALS-based metrics in this work. In study I, ALS-based surface metrics are assumed to describe forest land attributes better than straightforward ALS point cloud metrics. Used surface models were, for example, DTM, DSM, CHM and slope, curvature, wetness index, accumulation, hillshade and ruggedness calculated from DTM and DSM and classified CHM models calculated from CHM. Metrics were calculated based on the pixel values of each created surface inside the boundaries of circular plots and segments. In study III, horizontal landscape metrics were calculated from classified CHM and used to discriminate spatial pattern of trees and need for first thinning. CHM was classified in two classes: ground pixels and tree pixels. Metrics were calculated based on ground patches and tree patches within a microstand that comprised neighbouring ground and tree pixels. Landscape metrics usually describe the structure over a landscape and include measures such as area, fringe, shape, neighbourhood and homogeneity of landscape (McGarigal and Marks 1995). In study III, metrics were expected to describe the spatial pattern of trees and the stand density (need for thinning).

Texture metrics are used to express the spatial distribution of tonal variations within an image or any rasterised surface model (e.g. Haralick et al. 1973). Texture metrics were calculated in this work from ALS-based classified CHM (studies I and III) and from AI using pan-sharpared green, blue, and NIR bands (study II) and pan-sharpared NIR band (study IV). Texture metrics were calculated from the grey-tone spatial-dependence matrix using methods presented by Haralick et al. (1973). Only one grey tone spatial dependence matrix was created for each inventory unit (plot, segment, grid-cell). Parameter values used in calculations varied between studies.

Spectral metrics describe the spectral value and variation in a target area. In forestry, spectral and texture metrics are commonly used in forest type and tree species discrimination (e.g. Packalén and Maltamo 2007). Metrics are usually calculated directly from pixel values inside the boundaries of the target area. In this work, spectral metrics were tested for classification of forest land attributes, prediction of species-specific basal areas and detection of need for tending of seedling stands. Spectral metrics were calculated from AI in studies II and IV and from SI in study I. Except in study IV, spectral information was fetched from original (no pan-sharpared) bands to ALS points and metrics were calculated from pointwise mean values.

In study II, the specific interest was to use TSP from existing stand register data in prediction of species-specific basal areas. TSP were calculated from species-specific basal areas or numbers of trees in existing stand register data. A summary of used metrics (X-variables) in different studies is shown in Table 3.

4 RESULTS

4.1 Prediction of forest land and stand attributes

Forest land attributes. The classification of LU/LC class according to both national and FAO classification was highly accurate (study I). Similarly, classification of site type, peatland type and draining status succeeded moderately well (Table 4). The use of segments gave slightly better results in almost all classifications compared with the use of circular plots. In the classification of LU/LC, particularly horizontal ALS-based surface metrics calculated from DSM, played a major role as predictor variables. For example, shadow, slope and curvature conditions of the canopy in the forestry land or forest class had much more variation compared to the agricultural land and non-forest categories. As an example, values of the horizontal metric s_hills225_sdm (standard devation of the hillshade calculated from DSM) in classes forestry land, agricultural land and non-forest are shown in Figure 2a.

In this work, mineral soils and peatlands as well as undrained and drained forest land were discriminated for the first time using ALS data. The classification accuracies of main forest type and drainage status were only low and moderate. Despite this, the horizontal ALS-based surface metrics, especially those calculated from DTM, were important predictors. Differences were found, for example, in slope, curvature, ruggedness and some hydrological surface conditions between mineral soils and *peatlands* and undrained and *drained areas*. As an example, values of the horizontal metric a_slope_dtm (the average slope calculated from DTM) in classes mineral soil and peat land are shown in Figure 2b.

Spectral metrics calculated from SI played a more important role in the classification of site types than ALS-based metrics, especially metric b4b5 (NIR band divided by short wave infrared band). The richer the site type, the higher values produced. This indicates that a combination of band 4 and band 5 recognises the larger amount of deciduous trees and green vegetation on more fertile site types. From point cloud metrics, especially the proportion of intermediate echoes was often used, but also some height-related metrics appeared in models. Also, those metrics produced higher values, the richer the site type, except for the very rich site type.

It was only in the classification of peatland types that the point cloud metrics, especially density metrics, were found to be most significant predictor variables. For example, spruce peatlands got a higher proportion of vegetation hits than pine peatlands and open peatlands. This can be expected because spruce peatlands are denser than pine peatlands and open peatlands, which have very low canopy cover. Some ALS-based surface metrics calculated from DSM and CHM were also selected in best models.

Species-specific basal areas. In study II, the best accuracies for species-specific basal areas were obtained for Scot pine, Norway spruce and birches, which occurred abundantly in study areas and when all deciduous species were grouped together (see Figs. 4 and 5 in study II). RMSEs for deciduous species were quite high, which is typical for minor tree species. The use of TSP from stand register data improved the basal area prediction of different deciduous tree species (the case of seven different tree species) compared to use of ALS data and AI only (see Figs. 5 and 6 in study II). In the case of three tree species, differences were minor between used data sources. The use of metrics from all data sources (NN : all) could not substantially improve the accuracies of the predictions compared to methods, which utilised only ALS and stand register data. Two methods (LR and NN) were tested to utilise TSP from stand register data. Based on the results, both methods were able to predict species-specific stand attributes if the quality of the existing stand register data is adequate. The NN method was slightly better than the LR method in predicting basal areas for minor tree species.

Spatial pattern of trees. Classification of the spatial pattern of trees was highly accurate in study III (Table 4). Horizontal landscape metrics calculated from classified CHM were the best predictor variables in the identification of spatial pattern of trees, whereas point cloud and texture metrics were not as good predictors. The structure of the landscape like the area, size and number of tree and ground patches clearly correlated with the spatial pattern of trees. Clustered microstands consisted of large and continuous ground patches and smaller tree patches (group of trees) surrounded by ground patches. This is the opposite of random/regular microstands, which comprised large continuous tree patches and small ground patches. As an example, values of the horizontal metric $GP_{density}$ (the number of ground patches per hectare calculated from classified CHM) in classes clustered and random/regular are shown in Figure 2c.

4.2 Prediction of need for first thinning and tending of seedling stand

Classification of the need for first thinning was highly accurate in study III (Table 4) and both the horizontal landscape metrics and point cloud metrics were found to be significant predictors in identification of the need for first thinning. The pattern of both the landscape and point cloud metrics suggested that microstands that needed thinning were dense and had more uniform canopies compared to microstands with no need for thinning. The need for first thinning was determined correctly for almost all microstands, even if the spatial pattern of trees was determined incorrectly. As an example, values of the horizontal metric GP_{std} (the standard deviation of the size of the ground patches calculated from classified CHM) in classes no need for first thinning and need for first thinning are shown in Figure 2d.

In study IV, stem density (number of trees per hectare) was predicted with RMSE of 2204 stems/ha (49.7%) in validation data. The large RMSE can be partly explained by the very high stand densities in the area, which are caused by multi-stemmed deciduous trees and birches reproduced from the sucker shoots. The higher accuracies for tending need was obtained using plot data (kappa-values of 0.55 (LogR) and 0.71 (SVM)) compared with validation data (Table 4), even though results in ABA studies are usually more accurate at stand level. Plots and stands with the need for immediate tending and high density were easiest to classify correctly. In the LogR model one height, one density and one texture metric, and in the SVM model four height, two density and one intensity metric were used as predictor variables. High height values had negative and high density values had a positive correlation with tending need. Differences in classification accuracies between classification methods in validation data were minor.

Study IV also evaluated how large the error rates would be if 25 or 50% of stands with the most reliable predictions were left without field check. LogR was very good at correctly recognising the stand were prediction was reliable (100% correct in the case of 25% left out, and 91% correct in the case of 50% left out), but in the case of SVM, accuracies were clearly lower. However, the reliability of the SVM predictions is more difficult to assess, as a binary classifier does not have a clear probabilistic interpretation. Based on reliability analysis in whole validation data, 30% of the stands could have been left without a field check so that no errors would have been made (see Fig. 4 in study IV).

Table 4. Summary of classification accuracies of best models in studies I, III and IV. N = number of classes. Kappa = kappa-value, OA = Overall accuracy, * = cross-validated data, ** = validation data.

Classification	N	Kappa	OA %	Best metrics
Study I*				
National LU/LC	2	0.90	97	surface (+ point cloud)
FAO LU/LC	2	0.91	97	surface (+ point cloud)
Main type	2	0.37	90	surface (+ point cloud)
Site type 5	5	0.42	63	spectral (+ point cloud)
Site type 3	3	0.51	69	spectral (+ point cloud)
Peatland type	2	0.69	84	point cloud
Drainage status	2	0.52	88	surface (+ point cloud)
Study III*				
Spatial pattern of trees,	2	0.77	89	landscape
Need for first thinning,	2	0.93	96	landscape + point cloud
Combined	4	0.76	82	landscape
Study IV **				
Need for tending, LogR	2	0.38	71	point cloud + texture
Need for tending, SVM	2	0.37	72	point cloud

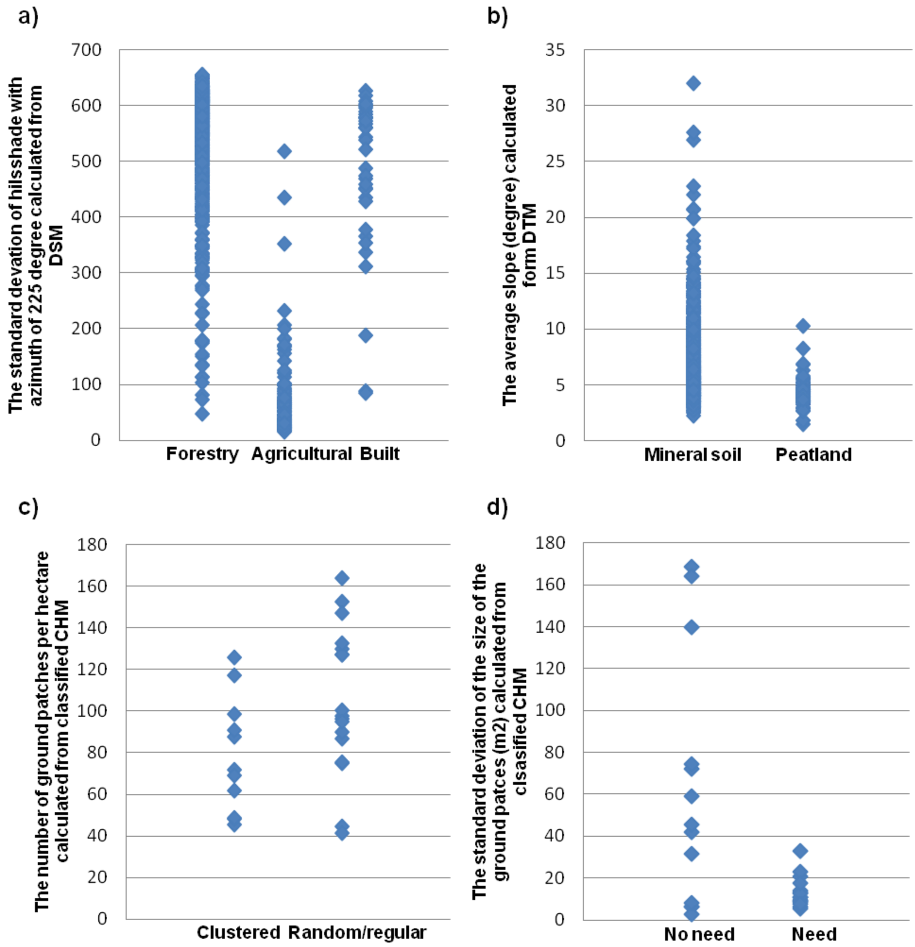

Figure 2. Values of the horizontal metrics s_hills225_dsm in classes forestry land, acricultural land and built (a), a_slope_dtm in classes mineral soil and peatland (b), $GP_{density}$ in classes clustered and random/regular (c) and GP_{std} in classes no need for first thinning and need for first thinning (d).

5 DISCUSSION AND CONCLUSIONS

5.1 Novel metrics and use of multiple data sources

The aim of this work was to develop ALS-based forest inventory for practical forest management by applying novel horizontal metrics and multiple data sources. In particular, this work examined the classification of forest land attributes (study I), prediction of species-specific stand attributes (study II), detection of spatial pattern of trees (study III), the need for first thinning (study III) and tending of seedling stand (study IV).

The point cloud metrics are nowadays the most commonly used predictor variables in ALS-based forest inventories. This work showed that horizontal ALS metrics calculated from ALS-based surface models could also be useful in forest inventory. Metrics were calculated from different ALS-based surfaces, such as DTM, DSM, CHM and different slope, curvature, wetness index, accumulation, hillshade, ruggedness and classified CHM models. In this work, horizontal ALS-based metrics were found to be good predictor variables, and even better than point cloud metrics, in the classification of LU/LC, main type and drainage status (surface metrics), and in detection of the spatial pattern of trees and need for first thinning (landscape metrics). This was the first time that horizontal ALS-based metrics were tested in the classification of forest land use attributes, detection of the spatial pattern of trees and need for silvicultural operations.

In RS of forest horizontal surface metrics are commonly calculated from AI or SI. In forest management inventories horizontal ALS-based metrics are rarely used as predictor variables, but ALS-based surface models have been useful in some applications. Earlier ALS-based DSM or CHM have been found useful in ITD (Hyyppä and Inkinen 1999), stand delineation (Koch et al. 2009) and evaluation of canopy cover and leaf area index (Korhonen et al. 2011); also, for example, in the classification of forest types and estimation of forest attributes (volume, biomass, Van Aardt et al. 2008) and in change detection (Vastaranta et al. 2012). Racine et al. (2014) studied the use of ALS-based metrics calculated from DTM (e.g. elevation, slope, aspect, catchment area, solar radiation and wetness index) in prediction of stand age, but they had only low or moderate importance in prediction models. Korpela et al. (2009) also used some metrics calculated from DTM in the classification of peatland (mire) types, but they found that point cloud metrics were more significant predictors. In some studies, forest land and different forest types have also been discriminated by utilising ALS-based surfaces, such as DTM, DSM, CHM and intensity rasters in classification (e.g. Antonarakis et al. 2008; Brennan and Webster 2006; Charaniya et al. 2004).

Based on this work, the possibilities of horizontal ALS-based metrics should be applied more in ALS-based forest research and practical inventories. Their potential should be tested for solving problems and weaknesses of ALS-based forest inventory, such as inventory of seedling stands, prediction of tree species, site types and forest structure. The potential of horizontal ALS metrics should also be tested outside of the scope of forest inventory, e.g. in habitat modelling, detection of biodiversity hot-spots and predicting non-wood forest products. In the future, the use of horizontal metrics calculated from high density ALS data and photogrammetric point cloud data also needs more careful examination.

This work also supported the earlier findings; the combined use of multiple data sources can offer great possibilities for more accurate and cost-effective forest inventory and management planning. So far, in practical ALS based forest inventory in Finland, the ALS data is used together with AI and field data to predict species-specific stand attributes (Maltamo and Packalen 2014). Study IV showed that the combination of ALS data and AI is also useful in ALS-based inventory of seedling stands. Height and density metrics of ALS data formed the base for tending need classification, but also texture metrics of AI were selected into the most accurate logistic model to provide additional information on characteristics of seedling stands. Spectral metrics from AI may also be useful in describing species proportions in seedling stands, although they were not significant predictors in study IV. Earlier, Korpela et al. (2008) classified seedling stand vegetation using a combination of ALS data and AI. Both ALS and AI metrics were selected into best models, but their conclusion was that their 27 vegetation classes could not be reliable classified using tested AI and ALS metrics (kappa-value 0.28).

Study I showed that forest land attributes can be classified using a combination of ALS data, SI and plots from NFI as training data. ALS-based metrics were used in most of the classification models, but SI-based metrics were most important in classification of site type. Metrics calculated from ALS data and SI were also used together in some of the models. Earlier, Hudak et al. (2006), Latifi et al. (2010) and Tonolli et al. (2011), for example, have predicted growing stock attributes using a combination of ALS-based and SI-based predictor variables. In study of Tonolli et al. (2011) combined use of ALS and AI clearly improved prediction of total timber volume and when data was stratified based on tree species, but in studies of Hudak et al. (2006) and Latifi et al. (2010) ALS-based metrics had superior role in prediction. The use of ALS data together with SI can offer great possibilities for prediction of forest land and other attributes also in practical ALS-based forest inventory. The possibilities of new optical satellite sensors (e.g. ESA 2015) might also increase the combined use of SI and ALS data for forest inventory. Using field plots from the NFI could increase the cost-effectiveness of ALS-based inventory, since separate field data does not need to be collected. In addition, the accuracy of the inventory will improve when the classification of forest land attributes are done by an experienced NFI field expert, not, for example, a seasonal worker. Earlier, Maltamo et al. (2009) and Tuominen et al. (2014) tested the use of NFI plot data in the prediction of growing stock attributes in practical ALS-based forest management inventories. The results of Maltamo et al. (2009) indicated that the accuracy of the estimates of stand attributes derived by using NFI training data was close to that of the fixed area plot training data. Tuominen et al. (2014) showed that adding NFI plots in the reference data generally improved the accuracy of the volume estimates by tree species but not the estimates of total volume or stand mean height and diameter. They discussed also that the difference between the plot types in the NFI and practical ALS-based management inventories causes difficulties in combination of the two datasets.

Study II showed that use of tree species information from existing stand register data could be useful auxiliary information when predicting species-specific stand attributes in ALS-based forest inventory. The utilisation of stand register data enables taking more than three tree species into account, and could also reduce data acquisition costs. Earlier Maltamo et al. (2006) tested combined use of ALS data, AI and class variables (main tree species, stand development class and site fertility class) from existing stand register data to predict plot volumes. That improved the RMSE of plot volume by 15 % compared to use of ALS data only. Närhi et al. (2008), in turn, used ALS point cloud metrics and stand age from existing stand register data to predict stem density in seedling stands with RMSE of 39 %. Breidenbach et al. (2010A) and Vastaranta et al. (2011) also tested existing developing class and site type and site type and tree species information for predicting species-specific stand attributes and thinning need, but those variables were not significant enough to be selected into final models.

Existing stand register data can offer many kinds of detailed information, such as TSP, stand age, site type or silvicultural operation history for ALS-based forest inventory, although the use of this data is not always trouble-free. Firstly, the conduction of different silvicultural operations, such as thinnings, and natural mortality dynamics usually mean that the inventory data is not up-to-date, even if the information has been updated using growth models. Hence, the accuracy of predictions depends on how much the forest structure has changed after field inventory. For example, after clear cut or certain thinnings, existing tree species information for stands is not valid anymore. This means that different kinds of treatments should be updated to the register. Secondly, the quality of existing stand register data is not always very good. For example, the data acquisition could have been non-comprehensive, e.g. by ignoring some minor tree species. This was also the case in study II, where information on some minor tree species was missing. Thirdly, in practical applications, there are usually some stands or large forest areas for which existing stand register data are missing. However, carefully collected and updated stand register data can offer accurate and detailed information for ALS-based forest inventories.

Nowadays several data sources such as ALS data, AI, SI, different kind of field data and existing stand register data are available for forest management. Data from different sources is suitable for different information needs and phases of inventory, for example ALS data for predicting growing stock and forest land attributes, AI and SI for tree species and site type separation and management history and age from existing stand register data for supporting prediction of silvicultural needs. In the future also different kind of GPS-located field data, such as tree lists from harvester data, might be possible to utilize in forest inventories. More research is still needed in this field, since the ability to combine data from different data sources (related to BigData) plays an important role in cost-effective forest inventory and management planning.

5.2 Evaluation of prediction of forest land and stand attributes

Forest land attributes. Study I showed that forest land attributes can be classified using combination of ALS data, SI and accurately measured field data, such as NFI plots. The use of segments gave slightly better results in almost all classifications than the use of circular plots. The reason for this may be that larger segments represent the characteristics of forest land and site type of the stand better than smaller plots. Promising results were obtained by using ALS-based surface metrics in the classification of LU/LC, main type and drainage status. Spectral metrics were found to be the most important variables in classification of site types and point cloud metrics in the classification of peatland types.

The high classification accuracies of forestry land and forest (LU/LC) in study I are in line with earlier land use classification studies where ALS-based surfaces have been used (Charaniya et al. 2004; Brennan and Webster 2006; Antonarakis et al. 2008). However, earlier studies are not straightforwardly comparable with this study due to quite different class definitions and used surfaces. In this study, classification accuracies of main type and drainage status were only low and moderate. One reason for the misclassification of peatlands may be that large proportions of the peatlands in the study area have changed very close to mineral soil because of successful draining and long time since drainage. Some characteristics of drained areas might not be detected either, because of overgrown ditches or a sparse ditch network. Differences among peatlands and among drained areas might also affect the difficulty of separating mineral soils and peatlands and undrained and drained areas. Earlier, only in the study of Dirksen (2013), point cloud metrics were used to separate peatland (swamp) forests and upland forests (non-paludified, mineral soil forest) with accuracy of 54-62%, but results are not totally comparable into study I. In study of Maxa and Bolstad (2009) use of lidar data improved the wetland/upland distinction based on relative terrain height and derived terrain-shape indices, which also supports findings in study I of the use of ALS-based surface metrics in separation of mineral soil and peatland.

The significance of spectral metrics calculated from SI and AI for the classification of forest types has been shown in many studies. Tomppo (1992) classified pixels into four site type classes using Landsat TM with OA between 50 and 70%, which are in line with accuracies of study I. So far only Vehmas et al. (2011) and Holopainen et al. (2010) have utilised ALS point cloud metrics in the classification of site types. Even though the field data of Vehmas et al. (2011) consisted of 247 mature forest stands on mineral soils, their classification accuracies were similar to the results of study I. Holopainen et al. (2010) used dominant height predicted from ALS data and stand age from stand register to determine the site index, and then converted site indexes into site types. Their results were also similar with study I. Compared to earlier studies combination of AI and ALS metrics were used in prediction of site types in study I.

Korpela et al. (2009) tested ALS-based features in the classification of mire habitats. Their classification accuracies of the main peatland (mire) types and dominant tree species are in line with our accuracies for peatlands. However, these studies are not fully comparable, because our classification consisted of pine-dominated, spruce-dominated and open peatland classes. They also found point cloud metrics to be the most significant predictor variables in classification models, and also intensity metrics in the separation of tree species.

In practical inventory applications, when predicting the forest land categories and site types, similar CHM based segments, such as the ones used in study III, can be delineated using automatic segmentation. However, because results of this work were only slightly better using segments in most of the classifications, the grid-based approach could also be applicable (see Fig. 4 in study I). Hence, in this study the plot level modelling unit was large enough to describe forest land characteristics in most cases. In addition to practical forest management inventory developed methods in study I could also be used in the national and international level to monitor the amount, properties and state of forests.

The classification of forest land attributes based on combination of different data sources still needs a more detailed examination in the future. Since the prediction of forest land and site types using RS is still challenging, the combined use of RS based predictions and information from existing land and stand register data could possibly be used in practical inventories. In addition, more detailed studies related to separating mineral soils and peatlands, detecting characteristics of peatland (mire) ecosystems and different site types using RS are needed.

Species-specific stand attributes. Study II showed that species-specific prediction of several tree species was more accurate when ALS data together with TSP from stand register data were used in prediction. This was expected because the separation of different deciduous species based on AI and ALS metrics is extremely difficult. The best accuracies for species-specific basal areas were obtained for dominant tree species. RMSEs for deciduous species were quite high, which is typical for minor tree species. In some specific study cases, such as dealing with biodiversity or urban forests, more important than accurate stand attribute estimates is the information about the existence of minor tree species. For example, in the forest of Turku city, the existence of hardwoods, such as oaks, is of primary interest for forest planning. Both the NN and LR methods were able to predict species-specific stand attributes, but the NN method was slightly better in predicting basal areas for minor tree species than LR. The NN method, which uses the species information of the chosen nearest neighbours, could be a better option if stand register data is less up-to-date or assessed less comprehensively, or if some minor tree species are ignored. Hence NN method is very well suited for mapping potential stands for certain tree species. Using NN stand attributes could also be predicted simultaneously for several depended variables, e.g. for several stand attributes and for several tree species. In turn using LR, which uses species information of each own stand, accurate species-specific attributes can be predicted, if stand register data is updated and comprehensively collected.

Packalén and Maltamo (2006, 2007, 2008) developed an ABA for species-specific stand attributes using the NN method, ALS data and AI. Similar prediction accuracies were obtained in study II for pine and spruce, but accuracies for deciduous trees were higher compared to their studies. One reason for this can be that the proportion of deciduous trees in their data was low. Our results are also in line with Breidenbach et al. (2010A, 2010B), who predicted plot volumes for several deciduous species using ALS data. Most of the ALS-based urban forest studies have focused on single tree level and on pure urban trees and gardens (e.g. Zhang and Qui 2011; Shrestha and Wynne 2012) or focused on tree species discrimination (e.g. Voss and Sugumaran 2008), and therefore cannot be compared to study II.

Study II showed that in forest areas with many different tree species, tree species-specific information can be predicted in more detail and with greater accuracy by using ALS and the existing stand register data, than by using ALS data and AI. It might be possible to use this approach in other areas, too. However, it would require the existence of reliable and up-to-date stand register data. Also, in managed boreal forests, the use of TSP from existing stand register data might be an alternative for AI, because the acquisition of AI is expensive and sometimes impossible (e.g. because of weather conditions) and especially if more detailed information on minor tree species is desired.

In principle, TSP from the stand register data can be utilised for the prediction of species-specific sum attributes (e.g. basal area, volume and number of stems), but they are not suitable for predicting the mean attributes of stands (e.g. mean height and diameter). Species-specific mean attributes of stand register data might be used in the prediction of current mean attributes. Another possibility is to calibrate the stand register based species-specific mean attributes by utilising the ratio of the predicted total mean estimate and stand register based total mean estimate.

An accurate and cost-efficient prediction of species-specific stand attributes is still an unresolved issue in RS based forest inventory. Hence, more research with new and innovative ideas to solve this problem is needed. Also, the combined use of RS and stand register data needs more careful examination, since the ability to combine data from different data sources and to update existing data plays an important role in cost-effective forest inventory and management planning.

Spatial pattern of trees. Study III demonstrated the successful identification of spatial pattern of trees using ABA. Classification accuracy of spatial pattern of trees was high and the horizontal ALS-based metrics were found to be significant predictor variables. The largest errors were detected in the classification of clustered microstands. The reason for that might be the high stand densities, in which case the tree groups and gaps could not be identified using ALS. However, incorrect classification of clustered microstands into regular/random ones is more consequential from a forest management point of view than vice versa. In study III, microstands consisted of rather young and equally sized trees (based on height) of the same tree layer, which may have had an effect on the results, in addition to a small number of observations.

Packalen et al. (2013) used ITD, semi-ITD and ABA, but their classification accuracies were comparatively low. In their study, similar landscape metrics as in study III were tested, but their field data was more heterogeneous compared to study III. The study by Mustonen (2002) applying ALS-based ITD provided correct spatial pattern for the majority of plots, excluding clustered plots. Both ALS-based studies of Mustonen (2002) and Packalen et al. (2013) reported the difficulty in detecting clustered spatial pattern of trees, which was also identified in study III. However, due to differences in the study material and methods applied, the results of these previous studies cannot be directly compared with study III. The approach presented should still be pursued in more detail in order to generalise results with a larger sample size, in more heterogeneous forests, and to identify all three spatial pattern of trees.

The detection of spatial pattern of trees using RS is a relatively unexplored area. This, together with the laboriousness of field measurements, is the reason why the detection of spatial pattern of trees will not be reasonable in practical ALS-based inventory in the near future. Based on results in study III, the need for first thinning was determined correctly for almost all microstands, even if the spatial pattern of trees was determined incorrectly. This indicates that there is no urgent need to determinate the spatial pattern trees if the need for thinning can be defined correctly without it. This, of course, changes if spatial information is also needed for other purposes such as for predicting growth or habitat modelling.

5.3 Evaluation of prediction of need of first thinning and tending of seedling stand

In study III, classification accuracy of the need for first thinning was highly accurate as the need for first thinning was determined correctly for almost all microstands. Both the landscape metrics and point cloud metrics were found to be significant predictors in the identification of the need for first thinning. In the case of tending of seedling stands (study IV), the classification accuracy was only moderate. However, based on this approach the amount of fieldwork required for seedling stands can be reduced. Height and density metrics were the most important in detecting the need for tending of seedling stands, but also texture metrics from AI was selected into best model. Surprisingly, the spectral metrics were not found to be important in detecting tending need, even though high NIR reflectance should indicate the dominance of deciduous species. The reason for this could be that most of the study area had fertile soils with plentiful herbaceous vegetation that is spectrally similar to deciduous foliage. However, it was difficult to find clear reasons for misclassifications, as there were errors in all kinds of plots and stands; but plots and stands with immediate tending need and high density were easiest to classify correctly.

The detection of silvicultural needs with RS is problematic since in practical forestry, such need is usually based on subjective field assessment of several attributes. When the need for silvicultural operations has been determined in ALS-based inventories, it has usually been done by means of estimated attributes of growing stock. Based on studies III and IV, it was done directly with ALS metrics. Direct classification is a more accurate alternative than the estimation of variables such as stem density (number of trees per hectare), spatial pattern of trees, species proportion and height differences, which all are evaluated when management decisions are made in the field.

High classification accuracies of the need for first thinning in study III are in line with the results of Halvarsson (2008) for thinning need and Nivala (2011) for fuel wood thinning need. Vastaranta et al. (2011) obtained slightly lower accuracies for thinning maturity. All three studies obtained good results using direct prediction and point cloud metrics as predictor variables, which support results in study III. In seedling stands, previous results for detecting the need for seedling stand tending (Närhi et al. 2008; Tahavanainen 2011) or predicting stand density (Næsset and Bjerknes 2001; Närhi et al. 2008) has not been very accurate. Those results are similar to study IV. In study IV field data was more comprehensive (including validation data) and also AI were utilized together with ALS data compared to earlier studies. Earlier Vastaranta et al. (2011) tested also tree species and site type as preliminary variables but they were not included in the final models. Närhi et al. (2008), in turn, utilised existing information of stand age in prediction of stem density in seedling stands. In study IV stand register data was not comprehensive and reliable enough to be able to utilise in prediction, which is a common problem in practical inventories. Study III and IV showed that in addition to traditional point cloud metrics, horizontal landscape metrics and AI metrics could also be used to determine the need for silvicultural operations.

There are several important issues that need to be considered in practical RS based seedling stand inventories based on the findings in study IV. Firstly, the training data should represent all kinds of seedling stands occurring in the area, which may be difficult to achieve due to limited recourses. Randomly selected plot locations may not cover the entire scale of ALS and AI features describing different seedling stands in the area. Thus, stratification is needed. Existing stand register data can help in stratification, but if it is out-of-date, it might take plenty of time to map different stand types of interest in the field. Solving this issue would require RS data to be already available in the plot selection phase, which is difficult as the fieldwork and RS data acquisition should be ideally performed at the same time. Secondly, the quality of field-based tending need estimates must be confirmed, since field measurements are often performed by short-term field workers. To be able to obtain reliable tending need estimates, field workers must be well-trained. Thirdly, it was found that the advantage of the logistic model is the probabilistic interpretation of the prediction, which assisted the detection of stands where the certainty of the predictions was high. Furthermore, results indicated that the selection of predictor features has a much larger influence than the selection of the classification method. Height and density metrics of ALS data forms the base for tending need classification, and texture metrics can provide additional information. In some cases, the spectral metrics may also be useful to describe species proportions, but they were not significant predictors in study IV. Fourth, the importance of obtaining a representative and consistently estimated base data that does not contain errors was also observed. Fifth, when the models are applied to predict the tending need for stands, the selection of the grid-cells that are used in the predictions is crucial. That is because existing stand borders may contain errors (e.g. mixed cells) and the presence of retention trees distorts the ALS height distribution for some of the cells. Results improved significantly when a height limit of 10 m was applied for prediction; i.e. cells including higher ALS height observations were excluded.

Although the analysis of seedling stands from RS data is a difficult task and some fieldwork is still needed, ALS-based predicted probabilities for tending need can be used to detect the stands for which prediction is reliable. These predictions should be combined with existing stand register data (such as site fertility, age and species) and local expert knowledge. If the predicted probability for tending need is high (need for tending) or low (no need) enough for a particular stand, and other available information supports it, then the cost of checking tending need in the field may be higher than the cost of possible errors. In the case of the need for thinning, its prediction seems to be more successful, but to get very accurate results stratification might be needed, because stand characteristics differ between development classes, tree species and site types. One reason for high classification accuracies in study I might be that microstands consisted of rather young and equally sized trees of the same tree layer. Many of the findings in study IV for inventory of seedling stands are also relevant for young and advanced thinning stands. However, more research is needed to improve the determination of need for silvicultural operations using a combination of RS and other data sources. In addition to improving the detection of the need for tending of seedling stands, other interesting topics are, for example, determining the need for complementary drainage, clearing of felling and thinning stands, pruning or fertilisation.

5.4 Conclusions

In this work, ALS-based forest inventory was further developed for practical forest management by applying novel horizontal metrics and multiple data sources. The results showed that it is possible to identify forest land attributes, spatial pattern of trees and the need for silvicultural operations using ALS-based forest inventory. Furthermore, the use of tree species information from existing stand register data proved to be useful auxiliary information when predicting species-specific stand attributes. Some of the successful results were obtained because of the use of novel horizontal ALS-based metrics and combined use of multiple data sources.

The inventory methods developed in this work for determining the need for silvicultural operations such as tending of seedling stands (and first thinning) are already in use in stand level forest inventories in Finland, and the experiences regarding their suitability in practice are collected. Similarly, the methods for combining ALS data and existing stand register data were developed simultaneously with the practical forest inventory of Turku city. Also, the identification of site types and forest land categories can be incorporated into the ALS-based forest inventory system, as presented in this thesis. The use of existing stand register data could also increase the cost-effectiveness of practical ALS-based forest inventory. To conclude, the combination of information from different data sources and emergence of novel metrics and statistical methods plays an important role in the development of cost-effective forest inventory and management planning.

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