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Forest mapping and monitoring using active 3D remote sensing

Mikko Vastaranta
Department of Forest Sciences
Faculty of Agriculture and Forestry
University of Helsinki

Academic dissertation

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Author: Mikko Vastaranta

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Thesis supervisors:
Prof. Markus Holopainen
Department of Forest Sciences, University of Helsinki, Finland

Prof. Juha Hyyppä
Finnish Geodetic Institute, Finland

Adjunct Prof. Hannu Hyyppä
Research Institute of Measuring and Modelling for the Built Environment, Aalto University, Finland

Dr. Mika Karjalainen
Finnish Geodetic Institute, Finland

Pre-examiners:
Prof. Barbara Koch
Department of Remote Sensing and Landscape Information Systems, University of Freiburg, Germany

Prof. Håkan Olsson
Department of Forest Resource Management, Swedish University of Agricultural Sciences

Opponent:
Prof. Timo Tokola
School of Forest Sciences, University of Eastern Finland

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ABSTRACT

The main aim in forest mapping and monitoring is to produce accurate information for forest managers with the use of efficient methodologies. For example, it is important to locate harvesting sites and stands where forest operations should be carried out as well as to provide updates regarding forest growth, among other changes in forest structure. In recent years, remote sensing (RS) has taken a significant technological leap forward. It has become possible to acquire three-dimensional (3D), spatially accurate information from forest resources using active RS methods. In practical applications, mainly 3D information produced by airborne laser scanning (ALS) has opened up groundbreaking potential in natural resource mapping and monitoring. In addition to ALS, new satellite radars are also capable of acquiring spatially accurate 3D information. The main objectives of the present study were to develop 3D RS methodologies for large-area forest mapping and monitoring applications. In substudy I, we aim to map harvesting sites, while in substudy II, we monitor changes in the forest canopy structure. In studies III-V, efficient mapping and monitoring applications were developed and tested.

In substudy I, we predicted plot-level thinning maturity within the next 10-year planning period. Stands requiring immediate thinning were located with an overall accuracy of 83%-86% depending on the prediction method applied. The respective prediction accuracy for stands reaching thinning maturity within the next 10 years was 70%-79%.

Substudy II addressed natural disturbance monitoring that could be linked to forest management planning when an ALS time series is available. The accuracy of the damaged canopy cover area estimate varied between -16.4% to 5.4%. Substudy II showed that changes in the forest canopy structure can be monitored with a rather straightforward method by contrasting bi-temporal canopy height models.

In substudy III, we developed a RS-based forest inventory method where single-tree RS is used to acquire modelling data needed in area-based predictions. The method uses ALS data and is capable of producing accurate stand variable estimates even at the sub-compartment level. The developed method could be applied in areas with sparse road networks or when the costs of fieldwork must be minimized. The method is especially suitable for large-area biomass or stem volume mapping.

Based on substudy IV, the use of stereo synthetic aperture radar (SAR) satellite data in the prediction of plot-level forest variables appears to be promising for large-area applications. In the best case, the plot-level stem volume (VOL) was predicted with a relative error (RMSE%) of 34.9%. Typically, such a high level of prediction accuracy cannot be obtained using spaceborne RS data. Then, in substudy V, we compared the aboveground biomass and VOL estimates derived by radargrammetry to the ALS estimates. The difference between the estimation accuracy of ALS–based and TerraSAR X–based features was smaller than in any previous study in which ALS and different kinds of SAR materials have been compared.

In this thesis, forest mapping and monitoring applications using active 3D RS were developed. Spatially accurate 3D RS enables the mapping of harvesting sites, the monitoring of changes in the canopy structure and even the making of a fully RS-based forest inventory. ALS is carried out at relatively low altitudes, which makes it relatively expensive per area unit, and other RS materials are still needed. Spaceborne stereo radargrammetry proved to be a promising technique to acquire additional 3D RS data efficiently as long as an accurate digital terrain model is available as a ground-surface reference.

Keywords: Forest inventory, forest management, laser scanning, LiDAR, synthetic aperture radar, radargrammetry

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Viikki, May 2012

Mikko Vastaranta

LIST OF ORIGINAL ARTICLES

This thesis consists of an introductory review followed by 5 research articles. Articles I-IV are reprinted with kind permission of the publishers, while article V is the author's version of the submitted manuscript.

I Vastaranta, M., Holopainen, M., Yu, X., Hyyppä, J., Hyyppä, H. and Viitala, R. 2011. Predicting stand-thinning maturity from airborne laser scanning data. Scandinavian Journal of Forest Research 26 (2):187−196. DOI: 10.1080/02827581.2010.547870.

II Vastaranta, M., Korpela, I., Uotila, A., Hovi, A. and Holopainen, M. 2012. Mapping of snow-damaged trees in bi-temporal airborne LiDAR data. European Journal of Forest Research 131 (4): 1217−1228. DOI: 10.1007/s10342-011-0593-2.

III Vastaranta, M., Kankare, V., Holopainen, M., Yu, X., Hyyppä, J. and Hyyppä, H. 2012. Combination of individual tree detection and area-based approach in imputation of forest variables using airborne laser data. ISPRS Journal of Photogrammetry and Remote Sensing 67: 73−79. DOI: 10.1016/j.isprsjprs.2011.10.006.

IV Karjalainen, M., Kankare, V., Vastaranta, M., Holopainen, M. and Hyyppä, J. 2012. Prediction of plot-level forest variables using TerraSAR-X stereo SAR data. Remote Sensing of Environment 117: 338−347. DOI: 10.1016/j.rse.2011.10.008.

V Vastaranta, M., Holopainen, M., Karjalainen, M., Kankare, V., Hyyppä, J. and Kaasalainen, S. 2012. TerraSAR-X stereo radargrammetry and airborne scanning LiDAR height metrics in the imputation of forest above-ground biomass and stem volume. Manuscript.

Authors' contributions

Mikko Vastaranta was the main author of articles I, II, and V. In article III, Mikko Vastaranta was the main author, along with Ville Kankare. In article IV, Mikko Vastaranta was responsible for the data collection, analyses and writing, along with Mika Karjalainen and Ville Kankare. All the articles were improved by the contributions of the co-authors at various stages of the analysis and writing process.

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ABBREVIATIONS

2D; 3D	2-dimensional; 3-dimensional
ABA	Area-based approach
AGB	Aboveground biomass
AGL	Above ground level
ALOS	Advanced Land Observation Satellite
ALS; LS	Airborne laser scanning; Laser scanning
a.s.l.	Above sea level
AVNIR	Advanced Visible and Near Infrared Radiometer
BA	Basal area
CHM	Canopy height model
CIR	Colour infrared
COSMO	Constellation of small satellites for the Mediterranean basin observation
CTP	Canopy transparency parameter
DCPA	Damaged crown projection area
DEM	Digital elevation model
Dg	Mean diameter
DTM	Digital terrain model
DSM	Digital surface model
dbh	Diameter-at-breast height
ERS	European Remote Sensing Satellite
FI	Forest inventory
GPS	Global Positioning System
GNSS	Global Navigation Satellite System
Hg	Mean height
InSAR	Interferometric Synthetic Aperture Radar
ITD	Individual tree detection
ITC	Individual crown approach, e.g. ITD
JERS	Japanese Earth Resources Satellite
LAI	Leaf Area Index
LASSO	Least absolute shrinkage and selection operator
LiDAR	Light detection and ranging
LVIS	Laser Vegetation Imaging Sensor
MGD	Multilook Ground Range Detected
MLS	Mobile laser scanning
MSN	Most similar neighbour
NFI	National forest inventory
NN	Nearest neighbour
PALS	Profiling airborne laser system
PALSAR	The Phased Array type L-band Synthetic Aperture Radar
Pol-InSAR	L-band polarimetric and interferometric SAR
R^2	The coefficient of determination
RF	Random forest
REDD	Reducing Emissions from Deforestation and Forest Degradation
RMSE	Root mean squared error
RS	Remote sensing
SAR	Synthetic aperture radar
SPOT	Système Pour l'Observation de la Terre
SWFI	Stand-wise field inventory
TanDEM-X	TerraSAR-X-Add-on for Digital Elevation Measurements
TCA	Tree cluster approach
TLS	Terrestrial laser scanning
UTC	Universal Time, Coordinated
VHF	Very high frequency
VOL	stem volume
WGS	World Geodetic System

INTRODUCTION

Background

Forests are mapped and monitored for multiple purposes. Forest resource information is gathered for large-scale strategic planning, operative forest management and pre-harvest planning. National forest inventories (NFIs) are examples of inventories undertaken for large-scale strategic planning for gathering information about nationwide forest resources, such as growing stock volume, forest cover, growth and yield, biomass, carbon balance and large-scale wood procurement potential. In NFIs, it is important to have unbiased estimates and obtain information also from small strata. The making of inventories of forest resources has a long tradition in Finnish forest sciences, making it among the first countries in the world to take such measures: a sampling-based forest inventory covering the whole country was introduced over 90 years ago (NFI 1, 1920-1924). Finnish foresters were also pioneers in developing new inventory methodologies when the making of multisource forest inventories was introduced in the early 1990s (Kilkki and Päivinen 1987, Tokola 1988, Muinonen and Tokola 1990, Tomppo 1991). However, operational forest management planning has been based on stand-wise field inventory (SWFI) for over 60 years in Finland. The potential of remote sensing (RS), such as the utilization of satellite – radar – and aerial images in the estimation of forest variables has been studied intensively, but the methodologies have not become generally used in practice. The reason is simple: the accuracy obtained in forest variable estimation at the stand level using RS data has not been adequate for forest management or pre-harvest planning.

During the last decade, RS has taken a significant technological leap forward, as it became possible to acquire three-dimensional (3D), spatially accurate information from forest resources using active RS methods. In practical applications, mainly airborne laser scanning (ALS) has opened up groundbreaking potential in natural resource mapping and monitoring (see Figure 1). ALS collects 3D information from forest resources, which enables a highly accurate estimation of tree or stand variables. For example, estimated root mean square error (RMSE) accuracies for total volume have ranged between 10% and 20% at the stand level in the Nordic countries (Næsset et al. 2004).

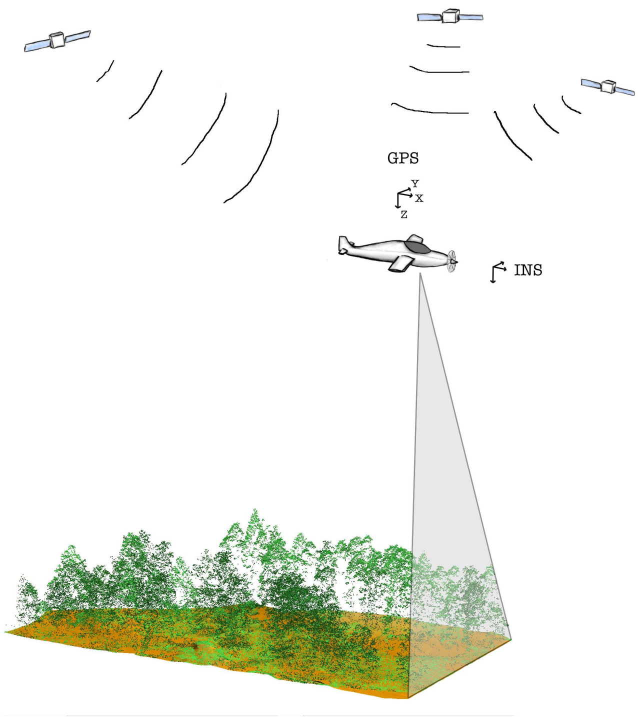

Figure 1. Principle of airborne laser scanning.©Ville Kankare.

ALS surveys are carried out at relatively low altitudes, usually from 0.5 to 3 km, which makes it relatively expensive per area unit. Other remotely sensed data will still be needed, especially when updated information is required annually. In addition to ALS, satellite radars, launched in recent years, are also capable of acquiring detailed 3D information for forest mapping and monitoring. Synthetic aperture radar (SAR) is a special case of imaging radars being able to provide images with the spatial resolution of about one meter from satellites, which are orbiting at an altitude of several hundreds of kilometers. An overview of the use of ALS, SAR, and hyperspectral remote sensing data for forest assessment can be found in Koch (2010).

Forest mapping and monitoring is carried out to support decision making by the forest owner. In operative forest management planning, input data have been traditionally gathered using SWFI. In SWFI, wood procurement potential, the amount of round wood removal and forest management proposals are mapped and determined. In addition to stand variables, site types are classified to map forest growth potential, the thinning regime, and biodiversity. Forest growth and yield are also highly correlated with forest estate value. The wood procurement chain from forest to users starts with knowledge of the stands available for harvesting. The accuracy of the SWFI data has not been adequate for mapping the thinning and final cutting sites, causing additional field work. In addition, preharvest measurements have been carried out separately based on existing SWFI.

In Finland, rather expensive SWFI endeavours have been carried out once every 10 years. In this case, updated forest resource information for the intermediate years is predicted using growth models. Another option is to use continuous updating in forest management, where forest stands are inventoried after each operation and the growth between operations is updated using growth models. However, neither of these methods provides an efficient means to monitor rapid changes in the forests.

Currently, the retrieval of stand variables, which is needed in forest management planning, is being replaced by ALS-based inventory methodologies in the Nordic countries. Relatively new ALS-based inventory methodologies were adopted quickly after the first promising studies (e.g. Nilsson 1996, Næsset 1997a, b, 2002, Hyyppä and Inkinen 1999, Hyyppä and Hyyppä 1999). The first operational test (6000 ha) in which an ALS-based inventory was carried out occurred in Norway in 2001. This test was followed by the first commercial contract for 46 000 ha in 2002. Various operational tests were carried out in Finland and Sweden during 2003 and 2004. In 2008, UPM-Kymmene acquired ALS data covering 450 000 ha of its forests. Forest inventories using ALS in privately-owned forests were first undertaken in 2010 in Finland, and by the end of 2011, almost 5 million ha had been scanned.

In operational wall-to-wall forest inventories, a two-stage procedure using ALS data and field plots, i.e. an area-based approach (ABA, Næsset 2002), has become common and a reference against which other inventory methodologies are compared. The foremost advantages of the state-of-the-art ABA compared to traditional SWFI are more precise prediction of forest variables and sampling-based estimation with the possibility of calculation accuracy statistics, and, at least in principle, ALS-based inventory does not depend on stand boundaries. Although current ALS data acquisition and processing costs are lower than that of traditional SWFI methods, ALS data is expensive compared to many other RS materials, and it is currently used mainly for the retrieval of basic forest inventory variables. Thus, improved means are needed to utilize it more efficiently in forest resource management, especially for large areas.

The mapping of potential harvesting sites is one of the key decisions for large-scale forest owners (Laamanen and Kangas 2012). Furthermore, monitoring applications related to forest growth and the mapping of natural hazards are required at varying scales. In large-area wall-to-wall applications, efficient methods are needed for accurate stem volume and biomass mapping. Thus, the fusion of ALS with other RS materials must be considered. This thesis contributes to these subjects.

Objectives of the study

The main aim in forest mapping is to produce accurate information from forest resources for forest managers with efficient methodologies. Methods are needed to monitor forest growth, among other changes in forest biomass, e.g. natural hazards and disturbances as well. The objectives of the present study were to develop active 3D RS methodologies for large-area forest mapping and monitoring applications. In substudy I, we aim to map harvesting sites, while in substudy II, we monitor forest canopy changes using ALS data. In substudy III, an efficient mapping application is developed using ALS data. In substudy IV, a method for the area-based mapping of forest variables is developed using radargrammetric 3D measurements, while in substudy V, the developed method is tested against state-of-the-art area-based estimation using ALS data. The specific objectives of studies I-V were as follows:

I An area-based approach is currently used in operational forest management planning inventory. Still, forest management proposals are made in the field by foresters. Here, we demonstrate a method to predict stand thinning maturity using ALS data. The method can be used for the mapping of harvesting sites.

II Multitemporal, spatially accurate 3D RS data sets are becoming more general, which enables novel monitoring applications. Here, we present a method for monitoring changes in the forest canopy structure using bitemporal ALS data.

III Single-tree remote sensing could be used to acquire the modelling data needed in ABA. Here, we demonstrate a fully RS-based forest inventory method. The method uses ALS data and is capable of producing accurate stand variable estimates even at the sub-compartment level.

IV Airborne laser scanning is relatively expensive per area unit compared to spaceborne RS data. Thus, other remotely sensed data will still be needed, especially in monitoring applications requiring high temporal resolution. A promising approach to map and monitor forest resources by radar imaging is radargrammetry. Here, we develop a radargrammetry-based method to predict plot-level forest variables.

V Here, we compare 3D information derived by ALS and radargrammetry to predict stem volume and biomass.

Laser scanning

Laser scanning in measuring forests

Laser scanning (LiDAR, Light Detection and Ranging; LS, Laser Scanning) is an active RS technique that uses the time-of-flight measurement principle to measure the distance to an object. With the known position of the sensor and precise orientation of these range measurements between the sensor and a reflecting object, the position (x, y, z) of an object is defined. The principle of LS measurements is the same regardless of the placement of the scanner. In forest mapping, the most frequently applied method is laser scanning done from an aircraft (ALS). Mobile and terrestrial laser scanning (MLS, TLS) have so far been used mainly for research purposes. From the forest mapping point of view, MLS could be linked to a logging machine to collect tree quality data, while TLS could be used in acquiring a plot-level reference. In this thesis, the applications of ALS are studied and MLS and TLS applications are discussed. The instruments used for ALS forest inventory purposes typically emit very short (3-10 ns), narrow-beamwidth (0.15-2.0 mrad), infrared (0.80-1.55 μm) laser pulses at near-nadir incidence angles (<30 degrees) with high pulse repetition frequencies (50-200 kHz). In general, when operated at flying altitudes of around 500 m to 3000 m, ALS sensors generate a dense sample pattern (0.5-20 pulses/m^2) with a small footprint (<1 m) on the ground.

A laser pulse hit on the forest canopy can produce one or more returns. In the simplest case, a laser pulse scatters directly from the top of the dense forest canopy or from the ground, resulting in a single return. Since the forest canopy is not a solid surface and there are gaps in the canopy cover, the situation becomes more complex when a laser pulse that hits the forest canopy passes through the top of the canopy and intercepts different parts of the canopy such as the trunk, branches, and leaves before reaching the ground. This series of events may result in several returns being recorded for a single laser pulse, which are referred to as multiple returns. In most cases, these multiple returns are recorded. Some systems record the full waveform of the reflected laser pulse as well. The first returns are mainly assumed to come from the top of the canopy and the last returns mainly from the ground, which is important for extracting the terrain surface. Multiple returns produce useful information regarding the forest structure (Hyyppä et al. 2009b).

The trunks, branches, and leaves in dense vegetation tend to cause multiple scattering or absorption of the emitted laser energy so that fewer backscattered returns are reflected directly from the ground (Harding et al. 2001, Hofton et al. 2002). This effect increases when the canopy closure, canopy depth, and structure complexity increase because the laser pulse is greatly obscured by the canopy. In practice, the laser system specification and configurations also play an important role in how the laser pulse interacts with the forest. For example, it has been found that a small-footprint laser tends to penetrate to the tree crown before reflecting a signal (Gaveu and Hill 2003); ground returns decrease as the scanning angle increases (TopoSys 1996); the penetration rate is affected by the laser beam divergence (Aldred and Bonnor 1985, Næsset 2004); a higher flight altitude alters the distribution of laser returns from the top and within the tree canopies (Næsset 2004); and the distribution of laser returns through the canopy varies with the change in laser pulse repetition frequency (Chasmer et al. 2006). Furthermore, the sensitivity of the laser receiver, wavelength, laser power, and total backscattering energy from the tree tops are also factors that may influence the ability of laser pulses to penetrate and distribute laser returns from the forest canopy (Baltavias 1999).

Two main approaches to derive forest information from ALS data have been used: ABA (Næsset, 2002) and individual tree detection (ITD) (Hyyppä and Inkinen 1999). In the former method, statistics calculated from the laser-point cloud are used as predictors and the retrieval of forest variables is typically based on nearest-neighbour (NN) or regression estimation using the laser-derived metrics and tree-by-tree measured field plots. With the ITD method, individual trees are recognized or segmented from the laser-point cloud, and tree-level variables are determined either straight from the point cloud or are estimated based on various other ALS features that are extracted for the tree segments using similar methodologies as in ABA. Beyond these two approaches, it is worth mentioning the tree cluster approach (TCA), which can be seen as a combination of these two.

Estimation of stand variables using an area-based approach

In the first ABA studies, single forest variables were predicted. Næsset (1997a) predicted stand mean height using the highest laser returns in grid cells within a stand. The use of all returns resulted in the underestimation of the mean height. Stand mean volume was predicted in Næsset (1997b) with regression. In the model, the predictors used were the mean height of the laser returns, laser-derived canopy cover, and mean height. Magnussen and Boudewyn (1998) calculated quantiles from the laser-point height distribution and used those as predictors of mean height. Later, these types of features were used in many ABA and ITD studies to predict variables of particular interest.

Hyyppä and Hyyppä (1999) predicted forest variables using area-based features as predictors. For the first time, ground elevation was subtracted from laser-point heights, which enabled the use of point heights as predictors that were directly comparable to the tree heights. In the study, ALS inventories were compared to various other optical RS methodologies, and it was concluded that ALS inventories had superior accuracy compared to others.

Næsset (2002) formulated data-specific regression models to predict forest stand variables using plot-wise tree-by-tree field-measured modelling data and laser-point height distribution metrics. With the developed models, stand variables were predicted for grid cells, and from them, stand-level variables were calculated. The standard deviation of the predicted stand variables varied between stand development classes and site types. The variations were 0.61 m−1.17 m in mean height (Hg), 1.37 cm−1.61 cm in mean diameter (Dg), 8.6−11.7% in basal area (BA), and 11.4−14.2% in stem volume (VOL). Models were formulated using 144 tree-wise measured plots, and the results were evaluated using 61 stands.

In Finland, the ABA was tested by Suvanto et al. (2005). Regression models were developed using laser height metrics for Dg, Hg, stem number, BA, and VOL of 472 reference plots. The predicted accuracies for 67 stands were 9.5%, 5.3%, 18.1%, 8.3%, and 9.8%, respectively. The predictions outperformed the accuracy of conventional SWFI (Poso 1983, Haara and Korhonen 2004, Saari and Kangas 2005, Vastaranta et al. 2010a). In forest management planning inventories in Scandinavia, species-specific information is needed for growth projections and simulated bucking. Tree species composition also has a major effect on forest value. The formulation of data-specific models for every strata is thus laborious, and NN-methodologies are more suitable for that estimation task. Maltamo et al. (2006) added features from aerial photographs and variables from existing stand registers as predictors, in addition to ALS height metrics and the NN imputation of VOL. The *k*-most-similar-neighbour (*k*-MSN) imputation method was used, and the plot-level VOL accuracy varied from 13% to 16% depending on the predictors used. Packalén and Maltamo (2007) used the *k*-MSN method to impute species-specific stand variables using ALS metrics and aerial photographs. Basically, they used the same dataset as in Suvanto et al. (2005), and the accuracies for species-specific VOLs at the stand level were 62.3%, 28.1%, and 32.6% for deciduous, Scots pine (*Pinus sylvestris*, L.), and Norway spruce [*Picea abies* (L.) H. Karst], respectively. Holopainen et al. (2010b) predicted timber assortment volumes with corresponding data and methodologies. At the stand level, the saw wood prediction accuracies (RMSE) were 79.2% (7.0 m^3/ha), 33.6% (35.5 m^3/ha), and 78.6% (6.2 m^3/ha), for Scots pine, Norway spruce, and birch, respectively. The respective accuracies for pulpwood were 167.6% (7.0 m^3/ha), 46.7% (11.4 m^3/ha), and 218.5% (25.8 m^3/ha). In the study, ABA was also discovered to provide slightly more accurate predictions for timber assortments than SWFI.

ABA has been intensively studied in the Nordic countries because of the practical need to replace SWFI. However, the methodology is applicable and has also been studied outside boreal forest regions. ABA has proven to be suitable for forest variable estimation in an alpine environment. Hollaus et al. (2007) obtained a cross-validated accuracy (RMSE) of 21.4% for VOL prediction, which is in line with Nordic studies. Hudak et al. (2007) tested several NN-imputation methodologies in ABA. They concluded that Random Forest (RF) was the most robust and flexible among the imputation methods tested. Latifi et al. (2010) tested ABA in a temperate forest for timber volume prediction. Their results strengthen the findings by Hudak et al. (2007). RF proved to be superior compared to other NN-methodologies, and the accuracies obtained were 23.3%-31.4% in plot-level timber volume prediction. In an ABA study conducted by Hawbaker et al. (2010), coefficient of determination (R^2) values of 65% for sawtimber and pulpwood volume, 63% for Hg, 55% for mean tree height, 48% for Dg, 46% for BA, and 13% for tree density were obtained in the state of Wisconsin in the U.S. Falkowski et al. (2010) imputed tree-level inventory data to parameterize a forest growth simulator. The results were validated with independent inventory data, and the root mean square differences in BA and VOL were 5m^2/ha and 16m^3/ha, respectively. They concluded that ABA was effective in generating tree-level forest inventory data from ALS metrics. Only a few studies have tested ABA in tropical forest conditions. Hou et al. (2011) compared ALS, Airborne CIR, and ALOS AVNIR-2 data sets to estimate VOL and BA in Laos. The prediction procedure followed Nordic experiences (e.g. Næsset 2002). In the study, ALS data proved to be superior, with an RMSE of 36.9% for VOL and 47.4% for BA. Integrating ALS metrics with other predictors from Airborne CIR or ALOS AVNIR-2 did not improve the prediction accuracies significantly.

Estimation of stand and tree variables with individual tree detection

ITD is based on detecting trees from a 3D point cloud (see Figures 5 and 8), and tree variables are either directly measured or predicted using derived ALS features. Hyyppä and Inkinen (1999) showed that, by segmenting tree crowns from the canopy height model (CHM), 40%-50% of the trees in coniferous forests could be correctly segmented. Persson et al. (2002) improved the crown delineation and were able to link 71% of the tree heights to the reference trees. The linked trees represented 91% of the total volume. When trees are detected by segmenting the CHM, only trees that contribute to the CHM can be detected (Kaartinen and Hyyppä 2008). Therefore, forest structure has a major influence on tree detection accuracy (e.g. Falkowski et al. 2008, Vauhkonen et al. 2012). Tree detection accuracy results from heterogeneous boreal forests are presented in Pitkänen et al. (2004), where the overall detection accuracy was only 40% (70% for dominant trees). Yu et al. (2011) presented an accuracy of 69% for tree detection in various managed forest conditions. These results are on a completely different scale from those in Peuhkurinen et al. (2007), where ITD was carried out for two mature conifer stands (density ~465 stems per hectare) and the number of harvestable trees was underestimated by only <3%, a result that may, however, include some commission errors (segmentation of a single tree into several segments). Koch et al. (2006) detected individual trees using a local maximum filter and delineated crowns using watershed analyses. The obtained results were encouraging in coniferous stands, but dense stands of deciduous trees were more problematic. Heinzel et al. (2011) used crown size as prior information for tree detection and improved the tree delineation accuracy by about 30% for deciduous and mixed stands compared to a non-crown-size-dependent algorithm. In general, CHM-based tree detection approaches are at their best in single-layered, mature stands (e.g. Peuhkurinen et al. 2007). Point-based approaches are needed to discriminate nearby or subdominant trees. However, this has proven to be a rather challenging task (e.g. Wang et al. 2008, Gupta et al. 2010, Vauhkonen et al. 2012). Tree detection errors were studied with 12 different ITD algorithms by Kaartinen and Hyyppä (2008) and with six algorithms by Vauhkonen et al. (2012). Kaartinen and Hyyppä (2008) concluded that the most important factor in tree detection is the algorithm used, while the effect of pulse density (2-8 returns/m^2) was observed to be marginal. In that study, all the algorithms were tested within two nearby study areas consisting of a few stands. In addition to several ITD algorithms, Vauhkonen et al. (2012) used test sites varying from tropical pulpwood plantations to managed boreal forests. Their main finding was that forest structure, such as tree density and clustering, strongly affects the performance of the tree detection algorithm used. The difference between algorithms was not seen to be as significant as in Kaartinen and Hyyppä (2008).

In ITD, tree-species classification has proven to be a challenging task, especially using only ALS data. Holmgren and Persson (2004) classified Scots pines and Norway spruces by their structural differences with >90% accuracy. In recent years, even more promising tree species classification results have been reported when high point density data has been used in combination with aerial images or ALS intensity. Liang et al. (2007) classified deciduous-coniferous trees in leaf-off conditions with an accuracy of 89.8%, taking advantage of differences in first-last pulse data. Holmgren et al. (2008) combined high-density laser data with multi-spectral images. Canopy-related metrics such as height distribution and canopy shape were calculated along with spectral features. A classification accuracy of 96% was achieved with 1711 trees. Vauhkonen et al. (2009) used solely high-intensity ALS data (~40 returns/m^2) and calculated so-called "alpha shape" metrics describing the canopy structure for the identification of tree species. The overall classification accuracy was 95%. When a method similar to that was tested with a larger data set (1249 vs. 92 trees) and a more practical point density (6-8 returns/m^2), an identification accuracy of 78% was obtained for three tree species (Vauhkonen et al. 2010). Korpela et al. (2010) obtained an 88-90% classification accuracy for Scots pine, Norway spruce, and birch using ALS intensity statistics. Puttonen et al. (2010) used illuminated-shaded area separation from aerial photographs combined with ALS data in tree species classification and achieved an overall accuracy of 70.8% with three species. Thus, taking the latest results into consideration, a solution for practical tree species determination can be said to be within reach, at least in the Nordic countries, where the number of commercially important tree species is rather low.

At the individual tree level, the most important variable is the diameter at breast height (*dbh*), from which the stem form, volume, and timber assortments are estimated. ITD yields direct information about tree height and crown dimensions, on which *dbh* predictions have traditionally been based (e.g. Kalliovirta and Tokola, 2005). The allometric relation between height and *dbh* is not as strong as the relation between *dbh* and height. Thus, *dbh* predictions based on tree height involve uncertainty.

More dense laser data has enabled the calculation of several laser height metrics for individual trees that can be used in the NN-imputation of tree variables (Villikka et al. 2007, Maltamo et al., 2009, Vauhkonen et al., 2010, Yu et al., 2011). These features are also used in tree species classification, as mentioned above. Maltamo et al. (2009) predicted tree variables, including tree quality variables, of Scots pines using *k*-MSN estimation combined with plot- and tree-level height metrics calculated from ALS data. The RMSEs for *dbh,* height, and volume were 5.2%, 2.0%, and 11%, respectively, when 133 accurately matched trees were used in the validation. The respective accuracies were 13%, 3%, and 31% in Vauhkonen et al. (2010) and 21%, 10%, and 46% in Yu et al. (2011). Vauhkonen et al. (2010) used 1249 trees and Yu et al. (2011) used 1476 trees for validation. In Yu et al. (2011) in particular, the mismatching of reference and laser tree candidates may have affected the results. Further, tree height determination from CHM is highly accurate but is prone to underestimation (e.g. Rönnholm et al. 2004). If the ground elevation and the uppermost proportion of a crown are not detected, then the tree height is automatically underestimated. Laser tree height is usually calibrated against field trees to reduce the bias caused by several scanning parameters and data processing steps such as the filtering used in producing surface models (see, e.g., Hyyppä et al. 2009a). However, as shown by the aforementioned studies, tree height is the most accurately determined variable in ITD.

Estimation of stand variables using a tree cluster approach

In the TCA, the CHM is first segmented, as in ITD. In the second phase, accurately located field trees are linked to the segments (Hyyppä et al. 2005, 2006, Lindberg et al. 2010, Breidenbach et al. 2010). In contrast to ITD, it is not assumed that a single segment represents a single tree (see Figure 8). In the TCA, all the field trees are linked to the nearest segment. Thus, segments may include no, one, two, or even more trees. All the other methodologies are adapted from ITD or ABA. The TCA requires accurate tree-by-tree measured reference data. Field trees used in the modelling have to be positioned with an accuracy that enables reliable linking to the corresponding CHM segments. The TCA could be described as an ABA that operates at the segment level instead of the grid level. Tree detection is the main error source in ITD (Vastaranta et al. 2011b). This method practically solves the tree detection problems, resulting in unbiased estimates for certain area levels. The TCA does not provide information as detailed as ITD could, in theory, but it is still capable of capturing the spatial variation in stand variables better than ABA. Lindberg et al. (2010) used the TCA to predict consistent tree height and stem diameter distributions. Breidenbach et al. (2010) obtained a plot-level RMSE of 17.1% for VOL compared to 20.6% with ABA.

Predicting forest growth and site type

ALS has a high geometric accuracy, which makes it suitable for monitoring forest growth (Yu et al. 2004). The growth of an individual tree can be monitored in several ways with two-time-point laser data: as differences in laser-measured tree heights (Yu et al. 2006), as differences in CHMs or digital surface models (DSMs) (Yu et al. 2004), as differences in laser height metrics (Næsset and Gobakken 2005, Vastaranta et al. 2011a), or as differences between tree volume estimates (Yu et al. 2008).

Yu et al. (2006) demonstrated that the growth of an individual tree can be measured with a standard error of only 0.14 m using multitemporal high-density ALS data (10 hits/m^2). The time period between the data acquisitions affect the accuracy of the measurements. In boreal forests, where the growth of stands is relatively slow, one-year growth is not measurable with a high degree of accuracy using either ALS or the traditional forester's field measurement equipment. Næsset and Gobakken (2005) observed statistically significant changes in bi-temporal ALS height metrics. However, the volume growth estimates had poor accuracy due to the short 2-year time interval between the ALS acquisitions. Yu et al. (2008) and Hopkinson et al. (2008) concluded that the longer the growth period was, the more accurate the growth detection would be. In temperate forests, Hopkinson et al. (2008) used multitemporal ALS data and showed that even annual forest *h*-growth was detectable. The relative standard error of the stand-level annual growth estimates was still high (ca. 100%) but decreased rapidly when the time interval was extended (~10% after 3 years).

Site-type classification is needed to describe the production potential of forest stands, select optimal harvesting strategies, and determine nature protection and recreational values. Site type can be predicted from laser data using height-over-age curves (Gatziaolis 2007, Holopainen et al. 2009, Holopainen et al. 2010c) or differences between site types in laser-point height distributions (Vehmas et al. 2008). Tree height measurements have been laborious, and it has not been practical to apply height-over-age curves for that reason. However, ABA and ITD are both at their best in measuring height-related variables as the dominant height (e.g. Hyyppä and Inkinen 1999, Maltamo et al. 2004, Næsset et al. 2004). The determination of stand age is more problematic if height-over-age curves are applied.

Gatziolis (2007) estimated the dominant height and site types with a single-tree-based ALS method in the coastal Pacific Northwest of the U.S.A. The ALS measurements were carried out in two campaigns, leaves on and off, with a pulse density of ~9/m^2. Single trees were detected with ALS, while stand age was derived from the forest management plan. The accuracy of age estimates was controlled with field sample plots. The coefficient of determination (R^2) between the site indexes derived from a field inventory or ALS measurements was 0.42. Wide variations in topography, as well as stand density, significantly affected the results, and far better results (R^2 0.88) were obtained when the data were filtered to include only average slopes and stand densities.

Vehmas et al. (2008) estimated mineral soil forest site types (five classes) with area-based ALS-inventory and the NN-estimation approach in a nature protection area in Finland. The hypothesis was that different forest site types would result in different vertical distributions of laser pulses due to the increasing numbers of deciduous trees on fertile site types. The best overall classification accuracy was 58%, and the best correct percentage for a single class was 73%. Vehmas et al. (2008) concluded that one source of error was the subjective determination of forest site type in the field, resulting in larger errors in ground truth than in the actual estimation with ALS data. Using a similar method, Vehmas et al. (2009) identified herb-rich forest stands from less fertile site types with an overall classification accuracy of 88.9%. Vehmas et al. (2008, 2009) did not carry out any ALS-based site indexing but estimated the forest site types directly. They also stated that this kind of approach is highly sensitive to the previous forest management and, thus, should be applied only in natural state forests.

Classification of site types has also been studied in mires. Korpela et al. (2009) tested mire vegetation and mire habitats, mapping possibilities using high-density laser data (10 hits/m^2). They concluded that laser-point height metrics combined with intensity information can be used in mire habitat mapping with a good degree of accuracy if local reference material is available.

Vega and St-Onge (2008) introduced a RS method for site index classification with promising results. The method was based on ALS and a time series of aerial photographs. In their study, the average bias of the site index and age was 0.76 m and 1.86 years, respectively. In the future, site indexing could be based on multitemporal ALS.

Holopainen et al. (2010c) determined the suitability of low-pulse density ALS and stand register data in the estimation of site indexes and site types via dominant height- and age-based site indexing. Dominant height was estimated with the NN method, and, for comparison, the dominant heights were derived directly from the distribution of ALS pulses. The site indexes were then estimated using models for artificially or naturally regenerated stands and converted to site types. The ALS-based site indexes were also compared with site indexes derived using field measurement data. The overall classification accuracy for the site classes was 70% in mature single-tree species stands. The method was sensitive to the stand age determination. The results of Holopainen et al. (2010c) suggest that forest site type and site index can be estimated nearly as well with an ALS-based estimation of dominant height as with field measurements involving single trees. However, further investigations are needed to develop methods for determining stand age and the functioning of site index models.

Site type estimation via site indexes provides a useful method for the determination of stand productivity. ALS-based forest mapping will open new opportunities for the implementation of site indexing in practice: in operative forest management planning, estimating the value of forest estates, and mapping ecologically important habitats.

Mapping and monitoring of forest management operations

In SWFI, forest management proposals for the next 10 years are determined for every stand. Proposals cover the whole rotation from renewal to the final cutting, and the timing varies from “immediate” to “rest” within the next 10-year period. When ABA is applied, only the forest variables are inventoried by RS, and forest management proposals are determined through additional field work. If laser data could be applied in the determination and timing of forest management proposals as well, it would enhance the efficiency of the ABA (Närhi et al. 2008, Vastaranta et al. 2010b, Räsänen 2010). Närhi et al. (2008) studied the inventory and determination of precommercial thinning in Norway spruce seedlings with low-pulse-density (0.5 hits/m^2) laser data. Seedlings requiring precommercial thinning were classified based on laser data with an accuracy rate of 71.8% with discriminate analysis. Räsänen (2010) used low-density laser data in determining micro-stand first-thinning maturity with a classification accuracy rate of over 97% without using separate test and training sets.

Forest management planning requires as accurate and up-to-date input information from forest resources as possible. ALS data were used in forest operation monitoring in, e.g. Yu et al. (2004) and Melkas et al. (2009). Change detection based on multitemporal ALS is even capable of detecting cut individual trees or branches (Yu et al. 2004). On-time ALS inventory data updating can be based on other information sources such as logging machine-gathered data (Melkas et al. 2009). Yu et al. (2004) used ITD and difference imaging of bitemporal CHMs to detect cut trees. With this method, 61 cut trees out of 83 were correctly detected. Undetected trees were mainly from the understory and did not contribute to the CHM.

Melkas et al. (2009) studied ABA- and ITD-acquired forest resource data updating, using species-specific timber volume information gathered with a logging machine. In a plot-level study, the accuracies (RMSEs) before the thinning were 21.6% and 21.7% with ABA and ITD, respectively. After the thinning, the timber volume information was updated using the logging machine data and the corresponding RMSEs were 29.4% and 31.6%. However, the absolute RMSE values stayed at the same level as before the cutting. They concluded that logging machine data has potential as a source of updated information at the stand level. Logging machine data also stores logging position, but it is not accurate enough to be used in tree-level data-matching.

Forest biomass and disturbance monitoring

One of the biggest challenges in programmes that aim to reduce global emissions from deforestation and forest degradation (e.g. REDD) is how to measure and monitor forest biomass and its changes effectively and accurately. Recent knowledge of forest biomass and changes in it is based on more or less subjective ground measurements and coarse- or medium-resolution satellite images. Therefore, the accuracy of biomass estimations, especially at the local level (e.g., in a forest stand), is poor. Stand biomass is highly correlated with tree heights, which can be determined accurately by ALS (Kellndorfer et al. 2010). ALS-based RS capabilities, such as the direct measurement of vegetation structure or tree and stand variables (e.g. Koch 2010, Holopainen et al. 2010a), should enhance the accuracy of the current biomass estimation means at all levels from single-tree to nationwide inventory applications.

The inventory of stands' above-ground biomass (AGB) can be based on single-time-point ALS acquisition. Multitemporal ALS can be used when monitoring biomass changes. Lefsky et al. (1999) showed that a single profiling LiDAR derived feature such as the quadratic mean of the canopy height could explain 80% of the variance in AGB. The structure of the forest canopy and the leaf area index (LAI) affects the penetration of the laser pulse in the crowns (Solberg et al. 2009). Changes in AGB have also been estimated using changes in LAI. The ground truth of LAI can be determined using a special measuring device or estimated from the ALS data (e.g. Solberg 2008, Solberg et al. 2006, 2009, Korhonen et al. 2011). Solberg et al. (2009) posited that LAI could use a relative number of ALS vegetation hits as a predictor and reported a correlation of 0.9 between ALS-derived and field-measured LAI.

Popescu et al. (2004) combined small-footprint ALS and multispectral data to estimate plot-level volume and AGB in deciduous and pine forests using ITD. The maximum R^2 values were 0.32 for deciduous trees and 0.82 for pines. The respective RMSEs were 44 t/ha and 29 t/ha. Bortolot and Wynne (2005) also used ITD in AGB estimation, and the correlation (r) varied from 0.59 to 0.82 and the RMSEs from 13.6 t/ha to 140.4 t/ha. Van Aardt et al. (2006) estimated forest volume and AGB with ALS point height metrics as predictors on a per-segment estimation. The adjusted R^2 and RMSE values for deciduous AGBs were 0.58 t/ha and 37.41 t/ha. Næsset (2004) used regression methods to estimate AGB for 143 sample plots in young and mature coniferous forests. The sample plot data was divided into three stratums (I: young forest, II: mature forest with poor site quality, and III: mature forest with good site quality). Regression methods explained 92% of the variability of the AGB covering all of these forest types. Jochem et al. (2011) used a semi-empirical model that was originally developed for VOL estimation to estimate AGB in spruce-dominated alpine forests. The model was extended with three canopy transparency parameters (CTP) extracted from ALS. The models were calibrated to the selected 196 sample plots. The R^2-values for the fitted AGB models were 0.70 without any CTP and varied from 0.64 to 0.71 with different CTPs. The standard deviations varied from 87.4 t/ha (35.8%) to 101.9 t/ha (41.7%). Latifi et al. (2010) tested ABA in southwestern Germany in timber volume and biomass mapping. They obtained accuracies of 23.3%-31.4% in plot-level timber volume and 22.4%-33.2% in AGB prediction, depending on the feature sets and feature selection used. Kankare et al. (2012) fused ITD and ABA in the imputation of plot-level AGB and VOL. The NN-estimation accuracies were 24.9% and 26.4% when field measurements were used in training the ABA. When ITD measurements were used in training ABA, the respective accuracies were 28.5%-34.9% and 29.2%-34.0%.

The determination of single tree biomass from ALS data has not been widely studied. One reason is that the acquisition of proper ground truth is laborious and requires laboratory analyses. Räty et al. (2011) made one of the pilot studies in modelling single-tree AGB using dense ALS data. In the study 38 trees consisting of 19 Scots pines and Norway spruces were analyzed in the laboratory after dense ALS data was acquired. Trees were segmented from the CHM and features used as biomass predictors were calculated at tree segment level. In linear regression, AGB estimation accuracy was 21% and 40% for Scots pines and Norway spruces, respectively.

The risk of forest hazards is growing partly because of climate change, which affects the natural forest dynamics. Damage caused by drought, snow, wind, and insects is more common. Forest damage can be monitored, e.g. by measuring changes in the leaf area index (LAI). This kind of approach is suitable for damage that causes defoliation. Solberg (2008) studied the use of multitemporal ALS in monitoring insect-related defoliation in Norway. Solberg had ALS data from three different time points and used changes in LAI as an indicator of defoliation. Solberg observed that the LAI values were high prior to the damage in July, as natural growth during the summer was also detected and affected the high values of LAI. Multitemporal data is expensive to use in practice. Thus, Solberg

(2008) proposed an indicator calculated for single-pass ALS data to be used in forest health monitoring. The proposed indicator was the relation between ALS-derived LAI and forest stand density.

Kantola et al. (2010) tested the use of ITD in the classification of defoliated and healthy trees using dense ALS data (10 hits/m^2) in conjunction with aerial images. Predictions were made using logistic LASSO regression, RF, and *k*-MSN. The classification accuracy ranged between 83.7% and 88.1% (kappa value 0.67-0.76). It should be noted that the trees used in the classification were clearly divided into healthy and defoliated trees, thus the results are not applicable to practice. However, the study proved that defoliated and healthy trees produce divergent point clouds and that the subject should be studied further.

Nyström et al. (2011) used bitemporal ALS data to classify changes in mountain vegetation. They used three treatments, the removal of 50% and 100% of the total number of stems above 1.5 m and a reference without any treatment. A rather high classification accuracy rate of 82% was obtained using only the proportion of vegetation returns as the predictor variable.

Large-area inventories

Laser scanning data is a far more expensive auxiliary data than, e.g., satellite images. Thus, strategic large-area forest inventories are still based either solely on field measurements (national level) or a fusion of field data and satellite images (county level). At the county level, ALS inventory has been studied. Næsset (2004) tested ABA in a 65 km^2 area in Norway. The accuracy of the predicted plot level volume was 17.5%-22.5% and the respective stand-level accuracy was 9.3%-12.2%. Holmgren and Jonson (2004) conducted a similar study in a 50 km^2 area in Sweden with a stand-level volume RMSE of 14.1%. In the aforementioned studies, ALS data covered the whole study area. In recent years, far larger areas have been inventoried operationally using ABA. At the national inventory level, it is not feasible to acquire wall-to-wall ALS data for forest inventory purposes. Holopainen and Hyyppä (2003) and Næsset et al. (2006) suggested the use of ALS data in strip-based sampling. There have been many studies in which profiling LiDAR has been used to acquire sampled forest inventory data (e.g. Nelson et al. 2003a, 2003b, 2004). Nelson et al. (2004) inventoried forest resources in the state of Delaware in the U.S. using 14 flight lines with a 4 km sampling distance. Their timber volume estimate at the county and state level differed from the U.S. Forest Service estimate by 21% and 1%, respectively. The corresponding differences in the AGB estimates were 22% and 16%. However, only a few studies have used a sampling procedure with ALS data. Gautam et al. (2010) used a two-phase sampling procedure to estimate the forest AGB in Laos. The procedure integrates sample plots with ALS transects (10% coverage tested) and satellite images, and it attains a relative RMSE of 25 to 35 percent in AGB in an area of 0.5 ha. The first sampling phase is based on full coverage by satellite imagery, and the second phase is based on ALS data and field measurements. A broad stratification is made based on satellite images. Then a sample of ALS transects are collected and the field plots are positioned based on ALS characteristics. Field plots are used to calibrate statistical models based on ALS. Finally, variables predicted using ALS models are used as references when estimation is carried out for a complete wall-to-wall area using satellite images. A somewhat similar approach was used in Gregoire et al. (2011) and in Ståhl et al. (2011) for a large-area forest inventory in Norway. They used NFI field plots, ALS transects, and profiling LiDAR data. The two-phase laser sampling estimates for AGB were close to the estimates predicted using only field plots. However, the corresponding standard errors were larger. Ståhl et al. (2011) obtained standard errors close to those of systematic field sampling with laser sampling. In this case, the predictions were overestimations. In both studies, profiling LiDAR and ALS were also compared, and the ALS was found to be more useful.

Acquisition of tree-wise field data using laser scanning

ALS is the most frequently applied laser system in forestry. However, in the acquisition of ground truth or in small-area monitoring, other applications such as TLS (Figure. 2) or MLS (Figure 3) are feasible.

TLS is usually done from a tripod with a scanner unit. The tripod is placed in the desired location and the scanner measures the 3D-locations of the targets within reach of the scanner. Scanners measuring phase-shifts are mainly used in measuring individual trees or field plots, while “pulse scanners” can be used in mapping larger areas with a maximum distance of around one kilometer to the target. TLS produces a dense point cloud from the surrounding trees. For example, with current phase-shift scanners, it takes 2-4 minutes to measure the surrounding area with a radius of 70-120 m, as the applied pulse density at a 10-m distance is still 6.3 mm. This corresponds to 25 000 points/m^2. From this dense point cloud, tree and stand variables such as location, height, crown coverage, species, and stem curve can be measured (Hopkinson et al. 2004, Pfeifer and Winterhalder 2004, Watt and Donoghue 2005, Henning and Radtke 2006, Holopainen et al. 2011a, Liang et al. 2011). Only the trees visible to the scanner can be measured; thus, tree density, visibility, and measuring geometry strongly affect how accurately tree variables can be measured (Liang et al. 2011).

Figure 2. Principle of terrestrial laser scanning. ©Ville Kankare

Forest plots are measured with one scan from the centre of the plot (Liang et al. 2011, Holopainen et al. 2011a) or with several scans around the plot (Hopkinson et al. 2004, Henning and Radtke 2006). In the single-scan mode, the amount of 3D data obtained is smaller and the field measurements are faster to carry out. The major drawback is that trees located in blind spots, i.e. shadowed by other trees, cannot be measured. In this method, the density of the point cloud depends on the distance to the scanner as well, affecting the modelling accuracy. In the multiscan mode, blind spots and problems of varying point density are reduced. However, additional work in the field and in post-processing, especially in the integration of several scans into a single point cloud, needs to be done. Automatic processing and forest measurements are currently being developed for TLS applications.

TLS provides a means of objectively collecting various tree and forest variables that are laborious to acquire with traditional means. Hopkinson et al. (2004) showed that TLS is capable of measuring forest stand variables. Vastaranta et al. (2009) used TLS to measure tree location accuracy with 0.1 m precision and tree *dbh*s with a standard error of 4.5% (8.3 mm). Liang et al. (2011) automatically mapped tree locations from single-scan TLS data, and 71% of the trees were detected correctly. However, unless processing of the TLS data and extraction of the basic tree variables is not fully automated, the strength of the TLS is in measuring tree variables other than the traditional ones. Various crown variables and even single branches are measurable in TLS data. Henning and Radtke (2006) measured tree stem diameters up to the crown-base height with accuracies <1 cm and <2 cm under 13 m of stem height. Pfeifer and Winterhalder (2004) modelled, in addition to stem diameters, branch diameters with an accuracy of better than 1 cm. Moorthy et al. (2008) determined in laboratory conditions the canopy gap fraction and LAI from TLS data with R^2 of 0.95 and 0.98, respectively. Hyyppä et al. (2009b) and Kaasalainen et al. (2010) conducted defoliation and biomass change measurements using TLS. The diminished number of point returns estimated the level of defoliation: the change in point returns correlated with an R^2 of 0.99 with a change in biomass. Holopainen et al. (2011a) modelled tree AGBs for Scots pines and Norway spruces. The stem and crown dimensions measured from the TLS point clouds correlated strongly (r 0.98-0.99) with laboratory biomass measurements carried out after scanning.

MLS can be seen as a method falling between ALS and TLS. MLS is laser scanning that is done from a moving vehicle such as a car or a logging machine. The application of MLS in forestry is being actively studied (Lin and Hyyppä 2010, Lin et al. 2010, Holopainen et al. 2011b, 2011c) (Figure 3). In the near future, MLS can be seen as a practical means to produce tree maps or inventories in urban forest environments. Holopainen et al. (2011b) obtained promising results with TLS and MLS compared with the accuracy of LS-based results and method efficiencies in Helsinki city street and park tree mapping. MLS and a logging machine could enable the automatic selection of harvestable trees and enhancements in stem bucking. However, MLS is still far from a widely used practical application in forestry, but the situation may change due to the rapid development of automatic MLS and TLS data processing.

Figure 3. Mobile laser scanning in Evo.

Satellite SAR imaging

Overview of relevant satellite SAR imaging techniques

Spaceborne RS data is typically needed when multitemporal information from large-area forest resources is required. An intriguing option is the use of inexpensive images with good temporal resolution that can be utilized in addition to ALS measurements in multiphase sampling and in the monitoring of changes in forest structure. In the Nordic countries, the sky is often covered by clouds and the amount of solar radiation is limited for long periods. This makes radar imaging, especially SAR carried by satellites, an interesting option in developing methods for forest mapping and in the monitoring of large areas. Compared with optical region satellite images, the major advantage of radar images is their temporal resolution under all imaging conditions, although, e.g., moisture affects to the image. SAR transmits a short pulse of microwave radiation − the wavelengths are typically between 3 and 25 cm − and then it records the backscattered signal from the illuminated target area. After the post-processing of raw SAR data, the result is a 2D radar image. A single SAR image includes information from radar backscattering intensity, the phase of the backscattered signal, and the range measurement between the radar antenna and the target pixel (Henderson and Lewis 1998).

Recently launched SAR satellites, TerraSAR-X, TanDEM-X, and Cosmo-SkyMeds, enable the acquisition of SAR images with spatial resolutions as high as 1-3 m. In addition to the improved spatial resolution, modern-day SAR-satellites enable advanced techniques such as SAR interferometry and SAR polarimetry, which are of interest in mapping forests.

Interferometry utilizes the interferogram generated from the phase differences of two SAR images taken from slightly differing positions. With the interferogram, a coarse 3D surface model of the landscape is obtained (Rosen et al. 2000). In forested areas, this interferometrically measured surface model is located somewhere between the ground and the tree canopies depending on the wavelength used. Longer wavelengths tend to penetrate deeper into the forest canopy (Balzter 2001). The quality of the interferogram can be evaluated by calculating a coherent image between two interferometric SAR images. In the case of a multi-temporal image pair, even small changes in the target, such as the movements of branches or needles, reduce the between-image coherence. For the extraction of elevation information, interferometry is at its best in digital elevation modelling (DEM) generation in poorly surveyed areas (e.g. Balzter 2001).

Polarization means the direction of the orientation of the electric field vector of the electromagnetic wave transmitted by the radar. In SAR systems, the vibration direction of the transmitted or received radio wave can be either horizontally (H) or vertically (V) polarized in relation to the antenna orientation. In full polarimetric imaging, all four combinations of transmit and receive (HH, HV, VH, and VV) are simultaneously recorded. The multiple polarizations can be used in image interpretation in ways similar to the multiple bands of an optical satellite image. The backscattering intensity of the cross-polarization bands (HV and VH) has proven to be a rather good estimator of the forest AGB: the greater the biomass is, the greater the backscatter at the cross-polarization band will be (Henderson and Lewis 1998). The main advantage of SAR polarimetry and interferometry for forest resource mapping and monitoring is that they allow the use of additional features, such as scattering mechanisms and the height differences of scatterers (Papathanassiou and Cloude 2001).

From the stand-level forest resource mapping point of view, an alternative to interferometry when extracting 3D elevation data from radar data is radargrammetry, which is based on the stereoscopic measurement of SAR images. It shares the same theoretical background as 3D stereophotogrammetric measurements, i.e., in radargrammetry, a stereo pair of SAR images with different off-nadir angles can be used to calculate the 3D coordinates for corresponding points on the image pair. The stereo-viewing possibility of radar images is not a new invention, as they were recognized already in the 1960s (see, e.g., La Prade 1963). The radargrammetric processing of SAR satellite data has recently been employed in a new way because of the improvements in SAR technology (Raggam et al. 2010). The spatial resolution of SAR data has improved so that it is now around 1 meter, which enables the extraction of more detailed DEMs than was the case with earlier SAR satellite data. With modern SARs, such as TerraSAR-X, it is possible to acquire images with varying off-nadir angles over the target area. Moreover, the direct georeferencing information of the SAR images has proven to be accurate and reliable (Ager and Bresnaham, 2009), enabling fairly effortless radargrammetric processing. Here, direct georeferencing refers to the solution of the orientation parameters of the imaging sensor using the Global Navigation Satellite System (GNSS) without ground control points.

SAR in forest mapping and monitoring

The Seasat satellite produced the first radar images obtained from a satellite as early as 1978, with a 25 m spatial resolution. In the 1980s and 1990s, the development of SAR satellite radars proceeded towards meeting aims set at a global scale: large-area applications without detailed information. In inventory applications based on SAR satellite radar images, the emphasis was on the estimation of large forest areas (e.g. Rauste 1990) and biomasses (e.g. Dobson et al. 1992, Le Toan ym. 1992, Baker et al. 1994, Rauste et al. 1994, Rauste 2006). During the last decade, SAR images have been used in plot- and stand-level forest variable estimation (e.g. Hyyppä et al. 2000b, Kellndorfer et al. 2003), as well as for monitoring forest operations (Ulander et al. 2005, Fransson et al. 2007). The results found by Hyyppä et al. (2000b) show that, with SAR data, to be precise using ERS coherence or JERS-1 L-band backscatter intensity, data accuracies similar to those of medium-resolution satellite images (Landsat TM) can be obtained. SAR data have been used successfully in large-area forest disturbance mapping. Ulander et al. (2005) mapped wind-induced forest damage using space- and airborne SAR. In that study, due to the coarse resolution and unfavorable wavelength (C-band), spaceborne SAR (Envisat and Radarsat) were not capable of detecting forest damage as well as long wavelength (3-15 m) airborne SAR (CARABAS-II) was able to detect damaged and even partly damaged forest areas. The spatial resolution (3 m) of CARABAS-II is similar to that of modern-day spaceborne systems. Clear-cut stands were separated from untreated stands using the backscattering coefficient in controlled experiments using multitemporal L-band ALOS PALSAR data with HH polarizations (Fransson et al. 2007).

The use of high-resolution radar image backscattering information in stem volume and AGB estimation has been studied quite intensively in recent years (Rauste 2006, Nelson et al. 2007, Tokola et al. 2007, Hyde et al. 2007, Holopainen et al. 2009a, 2010d). However, it has proven to be challenging because the SAR backscatter intensity is also affected by factors other than the forest AGB. Such factors are, e.g., terrain properties and target moisture content (Santoro et al. 2009). In addition, when assessing AGB, radar signals tend to saturate at certain AGB levels, resulting in the inability to estimate higher AGB quantities. The saturation level is dependent on the radar wavelength used and the forest structure (Santoro et al. 2009). Nelson et al. (2007) investigated pine stock biomass estimation by combining low-frequency (80-120 MHz) VHF RaDAR BioSAR and profiling LiDAR (PALS) data. The best R^2 and RMSE values for a linear regression model based on RaDAR features were 0.82 and 57.5 Mg/ha, respectively. The degree of determination of the respective single-feature profiling LiDAR model was 0.93 (RMSE 33.9 Mg/ha). The combination of the investigated sets of data improved the model's accuracy only slightly (R^2 0.94, RMSE 32.7 Mg/ha). Hyde et al. (2007) investigated the accuracy of stock biomass estimation in Southwestern Ponderosa pine (*Pinus ponderosa*) stands on the basis of profiling LiDAR, SAR, and InSAR data. The ground reference data comprised 52 circular sample plots. The biomass was estimated on the basis of a single-tree breast-height diameter and model-based approach. The mean canopy height derived from profiling LiDAR was able to account for most of the variance in the plot-level biomass (R^2 0.83, RMSE 26 Mg/ha). When stock biomass was predicted using GeoSAR/InSAR features derived from the P- (HH polarization) and X-band (VV polarization) responses and interferometric SAR height variables, the respective R^2 values decreased to 0.36 (RMSE 50.2 Mg/ha). By combining profiling LiDAR and GeoSAR X-P, the interferometric height increased the prediction accuracy only slightly (R^2 0.84, RMSE 24.9 Mg/ha). In a study conducted by Holopainen et al. (2010d), the estimation of VOL based on ALS data was far more precise than with TerraSAR-X data when they compared area-based laser-point height metrics and high-resolution TerraSAR-X dual-polarized (HH-HV or VH-VV) X-band backscattering intensity features in the estimation. The fusion of these data sources enhanced the results only slightly.

Banskota et al. (2011) investigated the estimation of deciduous and mixed-species AGB with scanning and profiling LiDAR and high-frequency (80-120 MHz) BioSAR-SAR data. The features derived from the LiDAR data were able to account for stock biomass better than those derived from the BioSAR-SAR data. The model's accuracy could be significantly improved by combining the two data sets. The best results were achieved by combining scanning LiDAR and BioSAR-SAR features (AGB estimation R^2 0.80 and RMSE 21.3 Mg/ha). Sun et al. (2011) investigated AGB estimation accuracy using ALS and SAR data (L-band polarimetric and interferometric SAR, Pol-InSar) in Howland, Maine, U.S.A. They found that Laser Vegetation Imaging Sensor (LVIS) data predicted field-measured biomass with a R^2 of 0.71 and RMSE of 31.33 Mg/ha. It was found that the SAR data can predict the ALS biomass samples with an R^2 of 0.63–0.71 and RMSE of 32.0–28.2 Mg/ha up to biomass levels of 200–250 Mg/ha. Their study showed the potential of the combined use of ALS samples and radar imagery for forest biomass mapping. Næsset et al. (2011) used ALS and InSAR data (Shuttle Radar Topography Mission, X-band) and model-based and model-assisted methods for AGB estimations from the stand to the district level. At the stand level, an independent validation on 35 field plots was carried out. RMSE values of 17.1–17.3 Mg/ha and 42.6–53.2 Mg/ha were found for ALS and InSAR, respectively. The RMSE% for the ALS estimations were 15%-17%, and for InSAR, the estimations were 42%-46%. Næsset et al. (2011) concluded that the examined RS techniques can provide more precise biomass estimates than a purely field-based sample survey.

It should be noted that a similar accuracy level to that of the 2D interpretation of aerial images or the use of optical region satellite interpretation can be achieved with 2D radar image features (e.g. Hyyppä and Hyyppä, 1999, Hyyppä et al. 2000b). This means that 2D methods are suitable for large-area applications, but not for sub-compartment-level mapping or monitoring. When this level of information is needed, the fusion of radar images and LiDAR (scanning or profiling) could be used (e.g. Nelson et al. 2007, Hyde et al. 2007, Holopainen et al. 2010d). Perhaps the most promising approach to determine forest AGB by radar imaging is via 3D canopy height information, similar to ALS. Nowadays, nationwide digital terrain models (DTMs) based on ALS are becoming available in many countries. Because ALS data includes many measurements from the ground surface, accurate DTMs for relating the radargrammetric measurements to the ground surface level exist. For example, Perko et al. (2011) used TerraSAR-X stereo radargrammetry to derive elevation models over forested areas and compared these models to ALS data. They concluded that the radar-based elevation values correlated with the forest canopy height values at the stand level, and the underestimation of the canopy height depended on the characteristics of the forest stand.

MATERIALS

Field data

Evo

Evo is located in Finland (61º19´N, 25º11´E, Figure 4). The area belongs to the southern Boreal Forest Zone and comprises approximately 2000 ha of mainly managed boreal forest. However, Evo is also a popular recreation area, which distinguishes it from totally homogenous managed forests and provides a cross-section from natural to intensively managed southern boreal forests. The average stand size in the area is slightly less than one ha. The topography of the area varies from 125 m to 185 m a.s.l. Scots pine and Norway spruce are the dominant tree species, as the site quality varies from groves to barren heaths.

Extensive field measurements were carried out in the Evo area during the years 2007, 2008, and 2009. The sampling of the field plots conducted in 2007 was based on the prestratification of existing SWFI data to distribute plots over various site types, tree species, and stand development classes. The plots measured in 2008 were located in harvested stands. In 2009, the stratification of the existing inventory data was completed. The plots (r=10 m) were located with GPS devices, and the locations were post-processed with local base station data. The following variables were measured for trees with a *dbh* larger than 5 cm: location, tree species, *dbh*, height, lower limit of living crown (only 2007), and crown width (only 2007). The stem volumes were calculated with standard Finnish models (Laasasenaho 1982). Plot-level estimates were obtained by summing the tree data. In substudy I, thinning proposals were determined in the field as in SWFI (Oksanen-Peltola et al. 1997). A summary of the used data sets and methods is presented in Table 1.

Hyytiälä

Substudy II was conducted in Hyytiälä in southern Finland (61°50´N, 24°20´E), which hosts a multitude of permanent forest plots that have been scanned five times since 2004 using ALS. The elevation of the studied forests ranges from 135 to 198 m a.s.l., which is quite high for southern Finland. In 2009, a large number of the forest plots were measured in support of RS research activity. In January-February 2010, the forest above 160 m a.s.l was subject to snow damage, which was most common in Scots pine stands. In 2010, ten pine-dominated plots that had been subject to varying degrees of snow damage were mapped (Table 1). The plots covered a total of 3.0 ha and were located in an 800 x 500-m area at 179.5-194.9 m a.s.l. The previous tree-wise measurements for these plots were made in the years 2006-2009, and the trees were positioned using a total station or a photogrammetric-geodetic method (Korpela et al. 2007). Damaged trees were identified in the field, and *dbh* measurements were updated for the plots, which had been measured before 2009. Using the previous measurements, it was possible to identify the events of the winter of 2010. All the plots represent forests in the thinning phase, with the mean age of the dominant trees ranging from 45 to 65 years. The site quality ranged from semi-barren (Vaccinium) to intermediate (Myrtillus type).

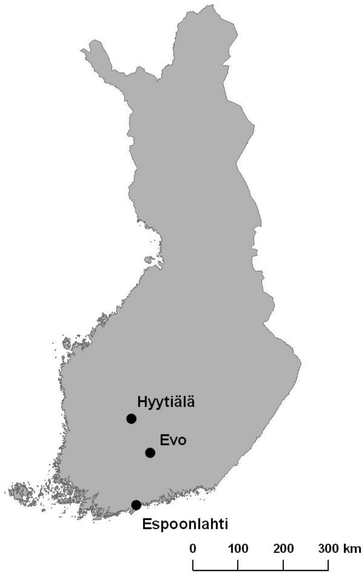

Figure 4. Map of Finland and location of the study areas.

Table 1. Summary of the data sets and methods used.

Study	Area	Number of field plots (area)	ALS	SAR	Estimation method
I	Evo	381 (314 m^2)	Yes	No	*k*-MSN, Logistic regression
II	Hyytiälä	10 (0.25–0.64 ha)	Yes	No	ΔCHM
III	Evo	509 (314 m^2)	Yes	No	*k*-MSN
IV	Espoonlahti	110 (201 m^2)	Yes	Yes	Random Forest
V	Espoonlahti	110 (201 m^2)	Yes	Yes	Random Forest

Espoonlahti

The study area used in substudies IV and V is located around Espoonlahti in Southern Finland, approximately 20 km west of the city of Helsinki (60°10'N, 24°36'E). In general, the topography of the test area can be described as undulating, with only slight variation in terrain elevation. The elevation values (heights above geoid) range from sea level (0 m) to approximately 50 m a.s.l. The forest in the study area is heterogenous semi-urban forest because the area is densely populated. The forests are also used mainly for recreation purposes.

Plot-level tree-by-tree field measurements for a total of 110 circular test plots (r = 8 m) were carried out in the fall of 2010. All the test plots were located in the same way as in the Evo study area. The *dbh* and tree species were determined for all trees with a *dbh* of more than 5 cm. Moreover, the height of every fifth tree was measured using a Haglöf Vertex clinometer (Haglöf Sweden AB, Långsele, Sweden) and the heights of all the trees were then modelled. The stem volumes and tree-level biomasses were calculated using models by Laasasenaho (1982) and Repola (2008, 2009). The plot-level estimates were obtained by summing the tree data.

Remote sensing data

Airborne laser scanning

Various ALS data sets were used in the thesis. Data were acquired in 2004, 2006, 2007, 2008, 2009, and 2010. The ALS data set from 2004 was used only for a DEM creation in the Hyytiälä study area. Detailed information from the ALS campaigns is presented in Table 2.

Table 2. Summary from the ALS data sets used.

Acquisition date year	**Area**	**Instrument**	**Altitude, AGL**	**Pulse density**	**Foot print, m (1/e)**	**Substudy**
2004	Hyytiälä	Modified Optech 1033	1200	1-2		II
2006	Hyytiälä	Optech ALTM3100	850	9.8	0.26	II
2007	Hyytiälä	Leica ALS50-II	800	7.0	0.12	II
2008	Espoonlahti		2000*	0.5*	0.5*	IV, V
2009	Evo	Leica ALS50-II	400	10	0.06	I, III
2010	Hyytiälä	LeicaALS60	1100	11.9	0.17	II

*According to the National Land Survey of Finland (2011)

Synthetic aperture radar

Detailed information on the TerraSAR-X images used is presented in Table 3. All the images were ordered as Multilook Ground Range Detected (MGD) products, i.e., non-interferometric data were used. All images were acquired within a period of two weeks in the spring of 2009.

Table 3. The list of TerraSAR-X SAR satellite images used.

Image#	**Acquisition date**	**Polarization**	**Orbit/ antenna direction**	**Incidence angle at scene centre**	**Time (UTC)**	**Resolution in ground range/azimuth (m)**	**Weather**
1	28.4.2009	HH/VV	Ascending/Right	35.8°	15:54	2.0/2.4	+19 °C, clear
2	29.4.2009	HH/VV	Descending/Right	36.1°	4:48	2.0/2.4	+10 °C, mostly cloudy
3	8.5.2009	HH/VV	Ascending/Right	51.7°	16:11	2.0/2.4	+16 °C, clear
4	11.5.2009	HH/VV	Descending/Right	52.0°	4:31	2.0/2.4	+9 °C, overcast

THEORETICAL OVERVIEW OF THE METHODOLOGIES USED

The processing of airborne laser scanning data

Creation of terrain, surface, and canopy height models

Laser scanning data is 3D point data in its discrete form with additional characteristics recorded for every return, such as echo type and intensity. The most frequently used method for the creation of a DSM is to take the highest first echo within a given neighborhood and interpolate the missing heights. After the creation of the DTM, a CHM can be calculated by subtracting the height of the ground from the DSM. The DSM is calculated from the highest echoes as the height of the ground, the DTM is calculated from the lowest. The accuracy of the DTM varies in forest conditions by around 10-50 cm (Kraus and Pfeifer 1998, Hyyppä et al. 2000, Ahokas et al. 2002, Reutebuch et al. 2003, Takeda 2004). The structure of the forest, variations in the terrain, and scanning parameters such as opening angle and pulse density affect the accuracy of the DTM (Ahokas et al. 2005).

Airborne laser measurements tend to underestimate tree height (Nelson et al. 1988, Hyyppä and Inkinen 1999, Lefsky et al. 2002, Rönnholm et al. 2004). The first echo return reflects more often from the shoulder of the tree instead of the top. Although a laser pulse hits the top, the tree top may not be dense enough to reflect a recordable return signal. On the other hand, dense under-vegetation causes overestimation in the DTM. Mainly for these reasons, the CHM is underestimated. Other factors affecting tree height measurement accuracy are flying height, pulse density, pulse footprint, modelling algorithms, scanner properties (e.g. sensitivity to record return signals, field of view, zenith scan angle, beam divergence), structure and density of the tree crown (Holmgren et al. 2003, Hopkinson et al. 2006).

Feature extraction unit

In RS based forest inventory, the feature extraction unit is usually a crown segment, grid cell, or microstand. Feature extraction in both ITD and ABA is based on a DTM (Figure 5) that is formulated from the lowest point heights. With DTM, the point heights can be normalized to represent heights above ground level. In ITD, the CHM (Figure 5) representing tree height is often used for tree delineation (Hyyppä and Inkinen 1999, Persson et al. 2002, Kaartinen and Hyyppä 2008, Vauhkonen et al. 2012). In the area-based prediction of forest variables, features are generally extracted from the ALS data at the grid level. The size of the grid cell is typically 100-900 m^2. The size of the grid depends on the purpose of the inventory and corresponds to the size of the reference plots. With a small grid size, ABA estimation comes close to ITD (Vastaranta et al. 2011a), as the large size can be equivalent to the whole forest stand (Næsset 1997a). The grid size used in operational forest management planning inventory in Finland is 16 m x 16 m.

Microstands can be used instead of a systematic grid in area-based feature extraction. Microstands are segmented automatically or semiautomatically using RS materials, such as CHM, aerial images, satellite images, or a fusion of these. A microstand is a spatially continuous, homogenous interpretation unit that follows the natural borders of the forests. In theory, natural borders are the advantage of using microstands over grid cells when the results are aggregated at the stand level. (Tuominen and Haapanen, 2011).

In ITD feature extraction, the unit is the tree crown area. Individual tree crowns can be segmented using ALS data or aerial images. The segmentation of aerial images is based on colour tones, while segmentation based on ALS data usually uses CHM 3D information.

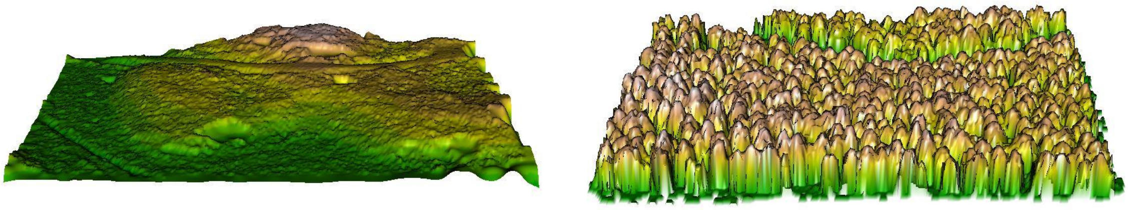

Figure 5. Digital terrain model (left) and corresponding canopy height model (right).

Geometric features

Tree variables can be measured directly from a laser point cloud. Traditionally, the characteristic geometric features have been the tree height and crown dimensions. The crown dimensions are determined by segmentation, as the tree height is the highest CHM value, or a laser return inside the segment. With dense ALS data (> 5 hits/m^2), it is also feasible to calculate various other geometric features to be used in estimating tree variables. These features describe the crown volume, shape, and structure (Holmgren and Persson 2004, Vauhkonen et al. 2010).

Vertical point height distributions

The prediction of stand variables in ABA is based mainly on point height metrics calculated from ALS data. Features such as percentiles calculated from a normalized point height distribution, mean point height, densities of the relative heights or percentiles, standard deviation, and coefficient of variation (Næsset 2002) are generally used.

The percentiles are down to the top heights calculated from the vertical distribution of the point heights, i.e., the percentile describes the height at which a certain number of cumulative point heights occur. The proportion of vegetation hits compared to all hits is also used as a predictor feature describing the crown density. A hit is seen as a vegetation hit from trees or bushes if it has been reflected from over some threshold limit above ground level. All the features are calculated separately for every echo type. The reason for this is that the sampling between echo types is somewhat different (Korpela et al. 2012). With dense ALS data, the predictors used in ABA and ITD have become similar (e.g. Villikka et al. 2007). The point height metrics that have generally been used in ABA are also used in the ITD approach. In ITD, these features are calculated at the tree crown level and used in the estimation of tree-level variables analogously to the estimation of stand variables in ABA.

The radargrammetric processing of SAR data

Extraction of point clouds from SAR stereo data

The most challenging part of radargrammetric processing is finding an automatic algorithm for seeking out the corresponding points (i.e. the tie-points) from the SAR image pairs at the level of single pixels.

Stereoscopic SAR measurement is demanding even when done manually due to the speckle and image distortions. An automated search of the tie-points can be done with area-based or feature-based methods (Zitová and Flusser, 2003). Area-based methods typically use a window of image pixels, for which the best matching location is searched from within a pre-defined area on another image. With the aim of finding the location giving the best matching, the cross-correlation value of the pixels in the pixel window in the various locations in the search window is typically calculated. If the cross-correlation value is higher than the selected threshold value at some point within the area examined in the second image, this point is considered to be a tie-point to the location shown in the pixel window of the first image. The feature-based methods rely on basic mapping entities, i.e., points, lines, and polygons. Still, even though a considerable amount of effort has been put into feature-based methods, area-based methods are most often used when images with the same sensors and similar imaging geometries are considered.

Obtaining above-ground elevations and predictor features from 3D points measured with radargrammetry

An accurate DTM is needed to derive above-ground point height values for stereoscopically measured 3D points. Currently, nationwide DTMs based on ALS are becoming available in many countries and provide a solid base for relating the radargrammetric measurements to the ground surface level. The accuracy of the radargrammetric points depends highly on the DTM accuracy. Radargrammetric heights are obtained in a similar way to the ALS normalized point heights, i.e., the height of the ground level is subtracted from the corresponding point height.

In this thesis, radargrammetric 3D features were extracted for plots with radii of 15 m. The radargrammetrically derived point density was ~0.03 hits/m^2, limiting the number of statistical features that are worth calculating. The following statistical features were calculated from radargrammetry point clouds: (1) the number of 3D points within a test plot, (2) the mean above-ground elevation of 3D points, (3) the standard deviation of the above-ground elevation values, and (4) the minimum and (5) maximum above-ground elevation values.

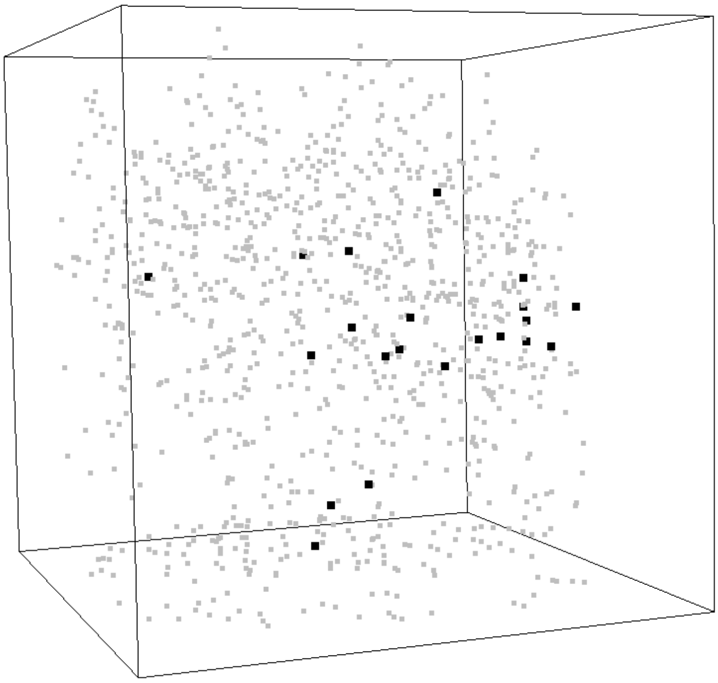

Figure 6. 3D point cloud from a forest plot. The grey dots represent ALS data and the black dots are 3D points derived from stereo SAR data.

Area-based approach

The area-based prediction of forest variables is based on a statistical dependency between the variables measured in the field and predictor features derived from RS data. In case of ALS, the method in which this kind of two-stage procedure is used to produce stand-level information from wall-to-wall grid-level predictions is called an area-based approach (ABA, Næsset 2002). In a more general context, two-stage predictions using field – and RS data has a long history in forest inventory (e.g. Poso et al. 1984), and it could also be called ABA. Thus, later, this two-stage prediction procedure with SAR data is also called ABA because it shares the same theoretical background.

When ABA is applied, accurate training data must be on hand (Poso et al. 1984, Næsset 2002). Training plots should represent the whole population and cover the variations in it as much as possible. The efficient selection of the training plot locations requires pre-knowledge of the inventory area (e.g. Maltamo et al. 2011). A sample unit in ABA is most often a grid cell, the size of which refers to the size of the field-measured training plot. Then the laser-derived features are extracted from the grid cell areas and used as possible predictors. The statistical relation between the predictors and response variables is modeled using training data when both of them are on hand. The response variables are predicted for grid cells without training data using regression or NN methods (Figure 7). If stand-level variables are needed, they are calculated by weighting the grid-level predictions inside the stand.

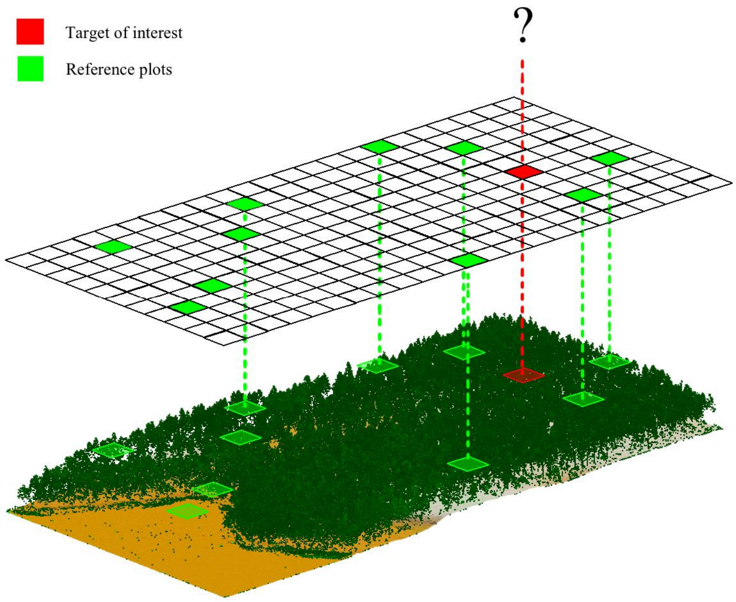

Figure 7. NN method. ©Ville Kankare

Individual tree detection

Individual trees can be detected from the laser-point clouds. There are two main approaches to detecting single trees from ALS data: point-based (e.g. Wang et al. 2008, Gupta et al. 2010) and surface model-based approaches (e.g. Hyyppä and Inkinen 1999, Persson et al. 2002). The main tree detection methods developed in boreal forest conditions belong to the latter and are usually based on finding local maxima on a smoothed CHM. After the local maxima are found, the boundaries of the crown are extracted, e.g., using a watershed-based region detector (Figure 8). The accuracy of the CHM and the corresponding accuracy of the ITD depend on the pulse density applied. A pulse density of around 5-6 hits/m^2 is seen as a prerequisite for the ITD, although even with pulse densities of around 2 hits/m^2, it is possible to detect individual dominant trees or tree groups (e.g. Breidenbach et al. 2010, Vastaranta et al. 2011c). Tree variables such as height and location can be measured directly from the laser-point cloud. The estimate for tree height can be the highest echo or the CHM value within the tree crown. The XY-location of the tree is generally the location of the tree top, i.e., the XY-location of the highest echo or CHM value.

Laser-based tree height is underestimated (e.g. Rönnholm et al. 2004) and usually calibrated using field data. Tree *dbh* cannot be measured directly from the point cloud and must be predicted. In *dbh* prediction, general allometric models (Kalliovirta and Tokola, 2005), local models (Peuhkurinen et al. 2007), or NN methods (Yu et al. 2010, 2011) can be used.

Besides tree height and crown dimensions, the use of other geometric features (Holmgren and Persson, 2004, Vauhkonen et al., 2010) and point height distributions (Villikka et al., 2007, Yu et al. 2011) has become more common in ITD predictions. In tree species classification, spectral features from aerial images or laser pulse return intensity are applied (e.g. Korpela et al. 2010). When NN methods are applied for the prediction of tree variables, training data is required. With respect to the plot level-training data used in ABA, ITD training data should cover the whole population variation at the tree level. However, ITD can be carried out without any field measurements if desired. In this case, missing variables are measured straight from the point cloud and/or modelled with existing models. Major error sources in ITD are the detection of the trees and the modelling of the missing variables, especially *dbh* and tree species classification (Holopainen et al. 2010a, Vastaranta et al. 2011b).

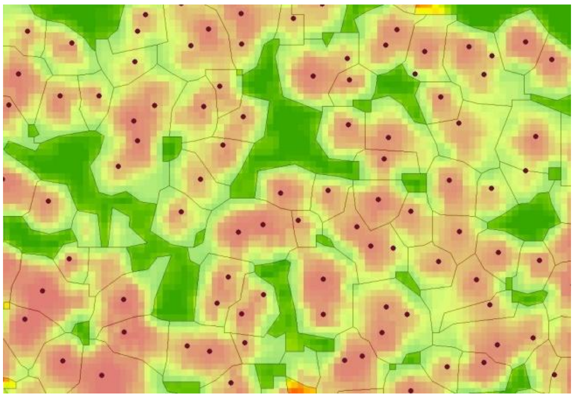

Figure 8. Trees crowns are delineated from the CHM (see Fig. 5) using watershed segmentation.

Multitemporal active 3D remote sensing data

Multitemporal active RS data provide a means of updating the forest data. Especially interesting are the possibilities for forest growth measuring, but it could also be utilized in the mapping of sudden large-scale disturbances. Multitemporal 3D data in monitoring tasks can be divided into methods that use changes in surface models (Yu et al. 2004, Hopkinson and Demuth, 2006, Vaaja et al. 2011), point height metrics (Yu et al. 2005, Næsset and Gobakken 2005, Hopkinson et al. 2008, Nystöm et al. 2011, Vastaranta et al. 2011a), or forest variables (Yu et al. 2008).

Independent inventories for two time points and observations of changes in the predicted variables is a basic mean of monitoring changes. This kind of approach can be applied in both ABA and ITD. The high geometric accuracy of the active RS data enables the contrasting of surface models from different time points. Difference imaging of DTMs is related to the detection of topography changes (e.g. Hopkinson and Demuth, Vaaja et al. 2011), as CHMs are related to changes in the canopy structure (Yu et al. 2004). These surface model-based methods are robust and the results are easy to interpret. The drawback is that only the phenomena that contribute to the surface model can be detected, i.e., harvested trees that do not contribute to CHM cannot be detected by contrasting CHMs. Change detection methods using point height metrics (e.g. laser point height distributions) from two time points also enable the detection of understory trees (Vastaranta et al. 2011a, Korpela et al. 2012) but are far more sensitive to changes in the implementation of the data acquisition parameters. Point height metric change detection methods can be used in ABA to monitor stand- or plot-level changes; as in ITD, tree-level changes can be monitored with similar means.

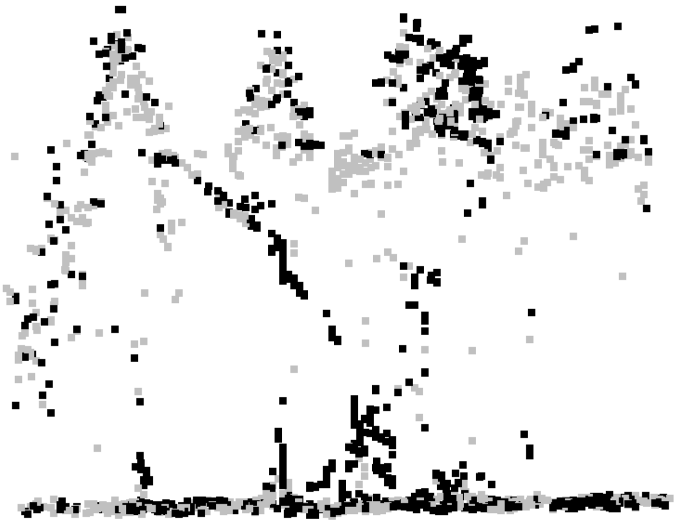

Figure 9. Effect of snow damage in a bitemporal laser point cloud (2007: grey; 2010: black). Minor height growth is also detectable.

Evaluation of results

The accuracy of the estimated continuous variables was evaluated by calculating the bias and RMSE:

$$BIAS = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n}, \tag{1}$$

$$BIAS\% = 100 * \frac{BIAS}{\bar{y}}, \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \text{ and} \tag{3}$$

$$RMSE\% = 100 * \frac{RMSE}{\bar{y}}, \tag{4}$$

where n is the number of plots, y_i is the value estimated from the field data for plot i, $\hat{y}_i$ is the predicted value for plot i, and $\bar{y}$ is the mean of the variable in the validation plots. In substudy III, the term “error” was replaced with “difference”. The performance of the thinning proposal prediction accuracy was evaluated by calculating the overall accuracy and kappa values. The omission and commission rates were used to evaluate ΔCHM methods in substudy III as well.

RESULTS AND DISCUSSION OF THE SEPARATE STUDIES

Predicting stand-thinning maturity from airborne laser scanning data

Forest variables are retrieved accurately with ABA for forest management planning purposes. However, much of the information needed in forest management planning must be collected in the field. For example, forest management proposals are often determined in the field by an expert. The mapping of harvesting sites is one of the key decision points for large-scale forest owners (Laamanen and Kangas 2012). In substudy I, the first tests were conducted to predict the thinning maturity of stands using ABA. The study was carried out in Evo, and the results were evaluated with 100 test plots located in young and advanced thinning stands. The ground truth regarding the timing of thinning was determined in the field by an expert. Stands that will reach thinning maturity within the next 10-year period (1) and stands in which thinning should be done immediately (2) were located using logistic regression and *k*-MSN. Logistic regression models based on ALS point height metrics predicted the thinning maturity with a classification accuracy rate of 79% (1) and 83% (2). The respective percentages were 70% and 86% with *k*-MSN.

The results here are comparable with the study conducted by Hyvönen (2002), particularly when a stand's operational need during the next 10 years is predicted. Hyvönen used Landsat TM satellite images and stand register data in a nonparametric *k*-NN estimation of forest stand variables and forest management actions. In substudy I, the classification accuracies were 79%, 70%, and 66% with the logistic ALS model, *k*-MSN, and the logistic model based on field measured forest variables, respectively, while Hyvönen obtained an accuracy rate of 64.1%. It should be noted that Hyvönen (2002) used far more inexpensive RS data, operated at the stand level, and that the reference and test sites were located in different areas. Substudy I demonstrated the feasibility of utilizing ALS data for predicting stand-thinning maturity. Although ALS data are a more expensive type of auxiliary data than satellite images, they are beginning to be widely available in many countries. Subjective expert knowledge was used in substudy I as a reference and that can be seen as a drawback. On the other hand, it enables one to use it in a wide range of forest conditions and thinning regimes, at least in theory. Närhi et al. (2008) also used ALS features in classifying a stand's precommercial thinning maturity with an overall accuracy of 71.8%. The results of their study are in line with those achieved here. However, precommercial thinning was not examined in this substudy. In general, the ALS-based prediction of forest management proposals could provide a practical future means of locating stands with operational needs.

Mapping of snow-damaged trees in bitemporal airborne data

Multitemporal ALS data is of interest in forest monitoring applications. However, short growing periods between ALS acquisitions have hindered the research. From that point of view, more rapid changes such as natural disturbances are easier to monitor. The snow-voluminous winter of 2009-2010 opened up the possibility of studying the use of bi-temporal ALS in snow damage mapping near the Hyytiälä forest research station. ALS data were acquired in years 2004-2010. The damage was documented in ten permanent Scots pine-dominated plots. To support method development, we examined the factors explaining the snow damage event at the tree level. We developed a ΔCHM-method (Figure 10) for the detection of snow-damaged crowns. In it, bitemporal ALS CHMs were contrasted and the resulting difference image was analyzed using binary image operations to extract the damaged crowns. Performance was evaluated by errors of omission and commission as well as the error in the estimated damaged crown projection area (DCPA). The method makes use of two threshold parameters, the required height difference (Δh) in the contrasted CHMs and the minimum plausible area of damage (mCC). The best-case performance was evaluated for these parameters and the optimal values were ~1.0 m for Δh and ~5 m^2 for mCC. The plot-level omission error rates were 19-75%, while the commission error rates were 0-21%. The relative estimation accuracy rate of the DCPA was -16.4-5.4%. The strongest predictors of snow damage were stem tapering, relative tree size, and local stand density.

We had dense, small-footprint ALS data, and the grid size in the CHMs was 0.5 m. Sparser data is likely to be used in practice for detecting corresponding damage. However, we assume that our method is not oversensitive to the pulse density applied, but its performance probably becomes less accurate at densities below 2-3 pulses per m^2. The average crown size is also an important factor, as it is linked to pulse density. In general, the larger and fewer the crowns are, the less dense the ALS data needs to be.

Vastaranta et al. (2011a) tested the area-based classification of snow damage with multitemporal ALS data (Figure 11). In the study, a forest area was divided into undamaged and damaged grid cells. The predictors used were the ALS point height change metrics, and stepwise logistic regression was used in the classification. The overall classification accuracy for the snow-damaged areas was 78.6% with a Kappa-value of 0.57. Vastaranta et al. (2011a) concluded that area-based estimation is also suitable for snow-induced change detection. Area-based estimation could also detect changes in trees that are not contributing to CHM, which is not possible with methodologies that only use changes in CHMs (substudy II).

The ΔCHM method is a potential tool for the monitoring of structural canopy changes in the dominant tree layer. Although the method was developed and evaluated in boreal Scots pine-dominated stands, it should be applicable to a wide range of forest conditions with different parameter values. Bitemporal ALS data are not widely available, and the acquisition costs for making a damage inventory would be substantial. Snow damage is a local phenomenon that is related to topography, while severe storm disturbances occur on a larger scale. Large continuous areas are needed for cost-efficient ALS campaigns, and the methodology proposed here is applicable under such circumstances.

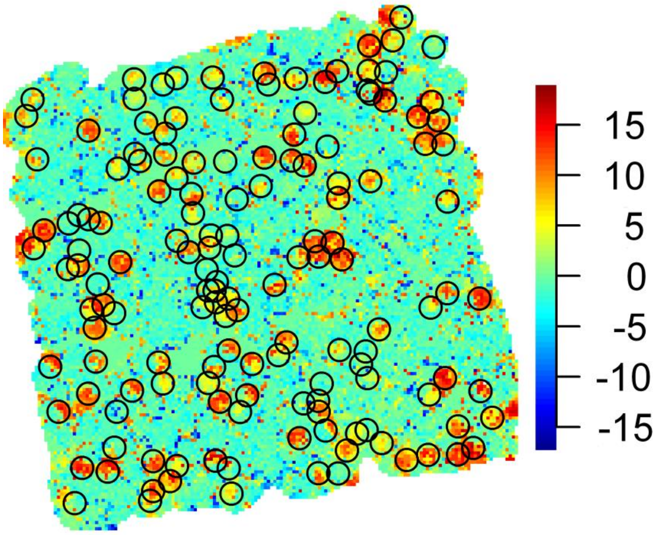

Figure 10. ΔCHM [m] of plot P_M_08. The colours range from −18 m to +19 m. Damaged trees were plotted, using black circles.

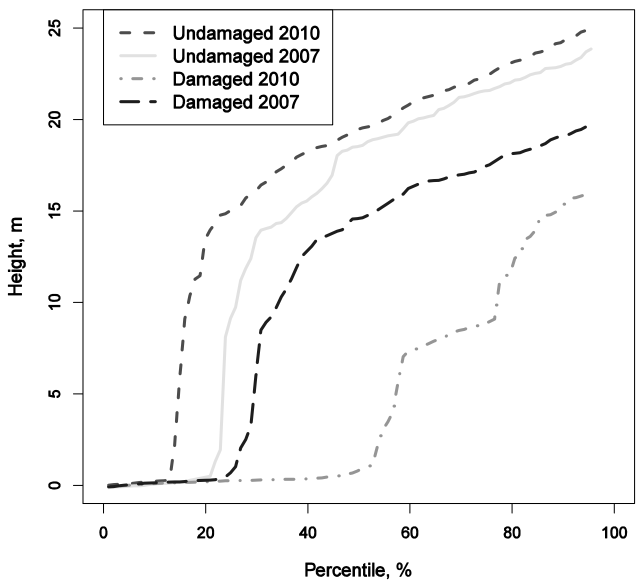

Figure 11. Effect of snow damage in grid-level point height distributions.

Combination of individual tree detection and area-based approach in imputation of forest variables using airborne laser data

The third substudy was a pilot study combining laser scanning inventory methods. ITD was used to measure training data for the ABA. In addition to automatic ITD (ITD_{auto}), we tested a combination of ITD_{auto} and visual interpretation (ITD_{visual}). ITD_{visual} had two stages: in the first, ITD_{auto} was carried out, and in the second, the results of the ITD_{auto} were visually corrected by interpreting 3D laser point clouds (Figure 12). The findings of previous studies encouraged us to test this kind of method fusion. The idea of performing visual interpretation from laser point clouds began with the tree detection problems with ITD_{auto} reported in many studies (e.g. Kaartinen and Hyyppä 2008, Vastaranta et al. 2011b). ITD_{auto} is usually carried out using only the CHM information, and the understory trees that do not contribute to the CHM are not detected. Visual interpretation is not feasible in a "wall-to-wall" inventory but could be utilized when acquiring training data. Our assumption was that the human eye can detect understory trees, separate closely growing trees, or drop commission errors easily from the whole point cloud compared with current ITD algorithms.

The RMSE in the imputed VOL was 24.8%, 25.9%, and 27.2% for the ABA trained with field measurements, ITD_{auto}, and ITD_{visual}, respectively. When ITD methods were applied in acquiring training data, the VOL, BA, and Dg were underestimated in the ABA by 2.7-9.2%. Contrary to our assumption, $ABA_{ITDvisual}$ did not provide more accurate results than the $ABA_{ITDauto}$. This phenomenon must relate to the number of nearest neighbours used in the estimation. Absolute accuracy within one field plot is not as crucial when the imputed variable is calculated as a weighted mean over several of the nearest neighbours.

Several ALS inventory studies have been carried out in the same area. Holopainen et al. (2008) estimated the plot-level VOL with a 27.1% RMSE using 282 field plots for training the *k*-NN method. The pulse density used was 1.8 hits per m^2 and the results were validated using leave-one-out cross-validation. Yu et al. (2010) obtained an RMSE of 56.5% for ITD (without any calibration) and 20.9% for the ABA. Their results were validated with 69 plots, and the pulse density used was 2.6 hits per m^2. In substudy III, a similar level of errors was obtained without any field measurements. However, the pulse density used was much higher (~10 hits/m^2) than those used in the aforementioned studies that favoured ITD, and although the method can be used without any field measurements, in practice, it might be feasible to use some tree level training data.

The developed method could be applied in areas with sparse road networks or when the costs of fieldwork must be minimized. The method is especially suitable for large-scale biomass or tree volume mapping.

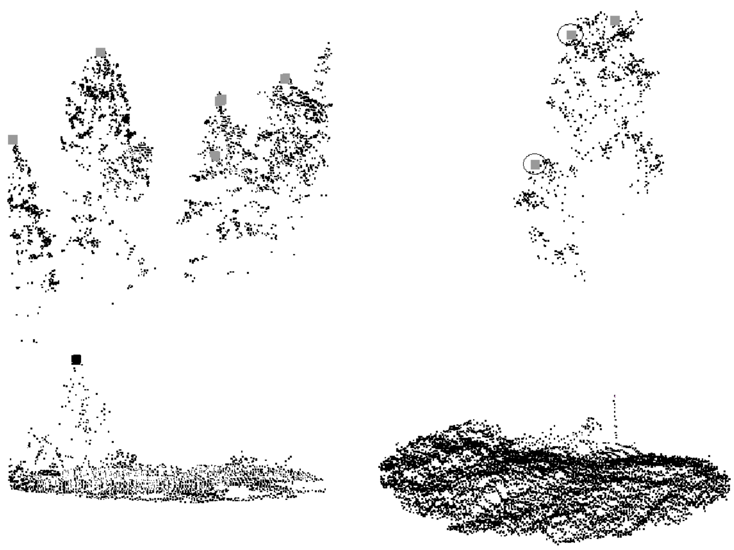

Figure 12. ITD_{auto}-detected trees plotted in grey. Left: Omission tree marked (black) from the understory. Right: Commission errors from a plot with a single tree are easily reduced in visual interpretation.

Prediction of plot-level forest variables using TerraSAR-X stereo SAR data

Spatially accurate spaceborne SAR data would be suitable for monitoring applications where a high degree of temporal resolution is needed. The promising results obtained by Perko et al. (2011) showed that X-band stereo SAR satellite data have potential in forest biomass mapping and monitoring even at the substand-level. The use of radargrammetry may also overcome the challenges faced in the estimation of forest variables using radar-intensity information. In radargrammetry, the problem of relating intensity information to forest variables is transformed into the problem of relating the extracted elevation values to forest variables. However, when information about the forest height is obtained, it is a parameter that is highly correlated with forest stem volume and AGB. In substudy IV, we developed a radargrammetry-based method to predict plot-level forest variables. 3D points were extracted from stereo SAR images (X-band TerraSAR-X satellite images) to be used as predictors in plot-level forest variable estimation (Figure 13). The extracted point height values appeared to be somewhere between the ground surface and the top of the canopy. Our estimation methodologies followed the standard ABA procedures that have been used with ALS data.

The RF method was used in prediction, providing relative errors (RMSE%) of 34.9%, 29.4%, 14.4%, and 20.5% for the VOL, BA, Hg, and Dg, respectively. In general, such a high level of prediction accuracy cannot be obtained using spaceborne RS data in the boreal forest zone. For example, Hyyppä et al. (2000b) compared SPOT XS, SPOT PAN, Landsat TM, ERS SAR, and JERS SAR data. The relative errors in VOL estimation varied from 45% to 65%. However, when the results of the stereo SAR data are compared to the ALS-based predictions presented in other studies, the relative error in the case of VOL is greater. ALS appears to be superior compared to stereo SAR data, mainly due to the much higher point density and lower penetration to the forest canopy. On the other hand, by adding more stereo pairs to the process, the number of 3D points could increase, slightly lowering the relative errors.

An alternative to radargrammetry when extracting 3D elevation data from radar is interferometry. It has also provided similar level of accuracies in forest variable prediction at the plot level (Solberg et al. 2010a; 2010b).Thus, 3D SAR data appears to be an interesting RS technique for future forest mapping and monitoring. Since SAR satellites enable the mapping of wide areas, there could be potential in producing detailed forest resource information even at the continental level. The 3D SAR data could also have high potential in forest monitoring, as the SAR-based features can be adapted to the methods currently used in operational forest inventories based on ALS data. However, further research is still needed to verify these results in other areas and compare this technique to the ALS.

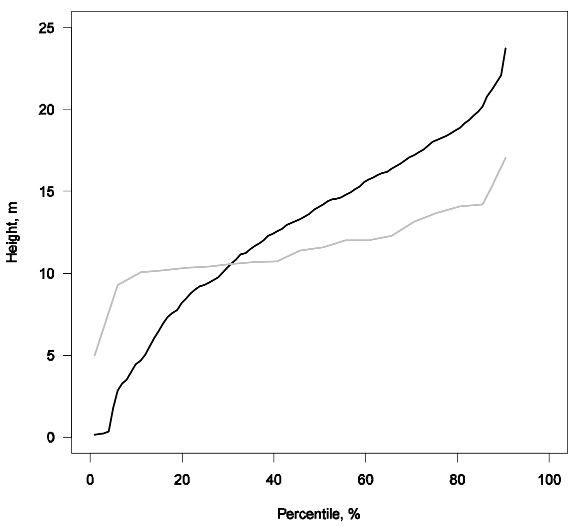

Figure 13. ALS (black) and radargrammetry derived (grey) point height distributions in one sample plot. ALS mean point height is 11.4 m as the respective radargrammetry height is 10.7 m.

TerraSAR-X stereo radargrammetry and airborne scanning LiDAR height metrics in the imputation of forest above-ground biomass and stem volume

TerraSAR-X stereo radargrammetry and sparse nationwide ALS data could be efficient methods for inventorying and monitoring AGB for large forested areas. Our objective in substudy V was to evaluate the AGB and VOL imputation accuracy when using ALS or TerraSAR-X stereo radargrammetry derived point height metrics as predictors in the NN estimation approach. To our knowledge, TerraSAR-X stereo radargrammetry has not been previously used in AGB predictions. Treewise measured field plots were used as reference data in the imputations and accuracy evaluations.

The DTM produced by the National Land Survey (NLS) of Finland was used to obtain above-ground elevation values for the TerraSAR-X stereo radargrammetry. The DTM used (grid size of 2 m) was derived from ALS surveys with an average point density of about 0.5 points/m^2. The respective DTM and point data were used in the ALS imputations. This kind of ALS data set will cover all of Finland in the near future.

The relative plot-level RMSEs for AGB and VOL were 29.9%. (41.3 t/ha) and 30.2% (78.1 m^3/ha) when using TerraSAR-X stereo radargrammetry metrics. The respective ALS estimation accuracy values were 21.9% (32.3 t/ha) and 24.8% (64.2 m^3/ha). The ALS imputations were undoubtedly more accurate than the imputations made by using TerraSAR-X stereo radargrammetry metrics. However, the difference between the estimation accuracies of ALS-based and TerraSAR X-based features were smaller than in any previous study in which ALS and different kinds of SAR data have been compared in forest variable prediction (e.g. Hyde et al. 2007, Holopainen et al. 2010d). This was our main finding. The future use of spaceborne SAR radargrammetry could be a cost-efficient method for spatially accurate large-area AGB mapping. It should be pointed out that the method requires accurate DEM, which is usually derived using ALS data.

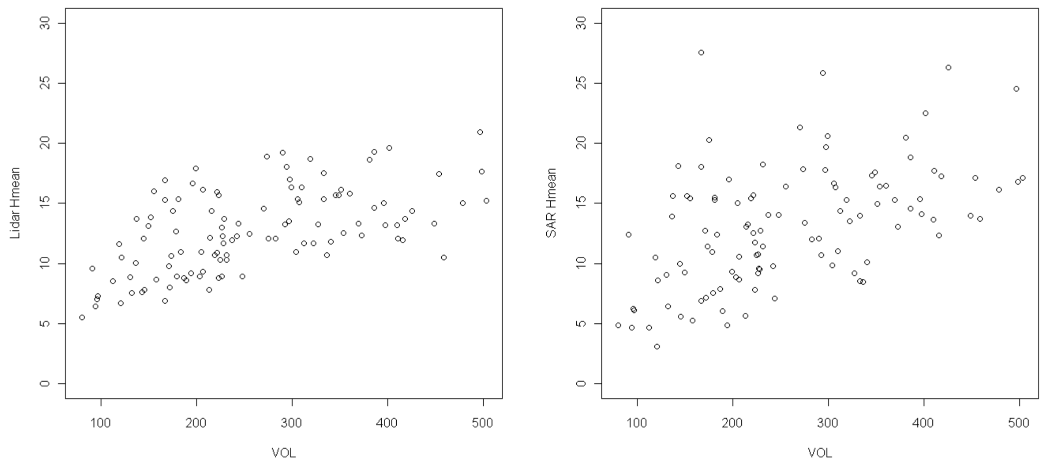

Figure 14. Field-measured stem volume (VOL, m^3/ha) plotted against ALS- and SAR-derived mean point heights (substudy V).

CONCLUSIONS

During the last decade, in forest mapping and monitoring applications, the possibility of acquiring spatially accurate active 3D RS information instead of 2D has been a major turning point. When the aim is to produce as accurate forest resource information as possible for forest managers, this change has opened up totally new possibilities. ALS is an efficient tool for 3D probing of the forest from above, and it is very promising concerning forest mapping and monitoring needs. However, the flying altitudes when acquiring ALS data are relatively low, which makes it expensive per area unit compared to spaceborne RS data. Other RS data is needed especially if updated information for forest monitoring is required with high temporal resolution. A promising approach to mapping and monitoring forest resources by radar imaging is the 3D techniques of interferometry and radargrammetry.

In this thesis, active 3D remote sensing forest mapping and monitoring methodologies were developed for large-area applications. In substudy I, we developed a mapping method to locate harvesting sites. In substudy II, we monitored forest canopy changes induced by snow damage. Monitoring applications could be the next turning point when spatially accurate multitemporal data sets become more common. The application potential in this field of forest monitoring is enormous and largely unexplored. In substudies III-V, efficient mapping and monitoring applications were developed and tested.

The mapping of potential thinning stands is the first key decision point for forest owners (Laamanen and Kangas 2012). The method developed in substudy I could be used in locating harvesting sites with reasonable accuracy. The method was evaluated at the grid level; thus, it is not dependent on stand boundaries. In substudy I, we predicted plot-level thinning maturity within the next 10-year planning period. Stands needing immediate thinning were classified with an accuracy rate of 83-86% depending on the classification method applied. The respective classification accuracy for stands reaching thinning maturity within the next 10 years was 70-79%. We used high-density laser data (10 hits/m^2), although the methodology applied could also be used with sparser data.

Multitemporal ALS data sets are uncommon and cover less than 10 years. Thus the general potential of ALS in monitoring applications using multitemporal data is largely unexplored. Study II addressed natural disturbance monitoring that could be linked to forest management planning when an ALS time series is on hand. Our results were very promising, but it should be noted that the data sets used were far more accurate than would be the case in the operational level. The accuracy of the damaged canopy cover area between plots varied from -16.4% to 5.4%. We conclude that ΔCHM is a potential method to monitor changes in forest 3D canopy structure with dense ALS data. However, the method developed could be applied with reasonable accuracy with more practical data sets. Natural hazards have also become more common in Finland, especially wind damage, and this kind of method is needed. From a practical point of view, it would be interesting to study the use of CHMs derived from ALS and SAR radargrammetry in forest disturbance monitoring.

Efficient wall-to-wall inventory means are required to provide accurate information about forest resources to managers. The ITD method has a strong physical background in measuring trees, and it is, thus, capable of measuring forest even without any field measurements. However, it is not generally used in operational forest inventory applications due to problems related to reliable tree detection in multilayered dense stands. During the studies of Vastaranta et al. (2011b), Vastaranta et al. (2011c), and Holopainen et al. (2010b), when the current ALS inventory methodologies were tested, we designed a method to combine ABA and ITD practically. Then we developed a fully RS-based forest inventory method in which single-tree remote sensing (ITD) is used to acquire the modelling data required in ABA. The method uses ALS data and is capable of producing accurate stand variable estimates even at the sub-compartment level. The method developed could be applied in areas with sparse road networks or when the costs of fieldwork must be minimized. The method is especially suitable for large-area biomass or tree volume mapping.

Promising results have been achieved recently in the matter of the automated processing of stereo SAR satellite images in the endeavour to obtain elevation data. Perko et al. (2011) showed that modern-day X-band SAR satellites with a spatial resolution of about 1 m can provide quite accurate elevation data in open areas and concluded that, in forested areas, stereoscopically measured elevation data appears to be correlated with forest canopy height. These results encouraged us to study the prediction of plot-level forest variables using elevation information obtained from stereo SAR data in substudy IV. According to the results we obtained, the use of stereo SAR data in the prediction of plot-level forest variables appears to be promising. Using the RF method, a relative error (RMSE%) of 34.9% was obtained for stem volume prediction. For the other forest variables, i.e., the BA, Dg, and Hg, the accuracies were slightly better, 29.4%, 14.4%, and 20.5%, respectively. Typically, such a high level of prediction accuracy cannot be obtained using spaceborne RS data in the boreal forest zone.

In operational wall-to-wall forest inventories, ABA has become common, and it is seen as a reference against which other methodologies are compared. In substudy V, we compared the AGB and VOL estimates derived by radargrammetry with ALS estimates. The forest AGB estimation accuracies based on TerraSAR-X stereo radargrammetry features were better than in previous studies. Furthermore, it should be noted that the difference between the estimation accuracy of ALS-based and TerraSAR X-based features were smaller than in any previous study in which ALS and different kinds of SAR materials have been compared. Thus, it can be concluded that TerraSAR X stereo radargrammetry is promising as RS material along with single-pass SAR interferometry (e.g. the on-going German TanDEM-X mission) for large forest area AGB mapping and monitoring when accurate ALS-based DTM/DEM is available. In theory, SAR interferometry could provide even more accurate height measurements than radargrammetry. However, the interferometric height measurements are problematic in various forest conditions compared to the robust radargrammetry.

In this thesis, forest mapping and monitoring applications using active 3D RS were developed. The substudies covered a wide range of applications, and many of the suggested methodologies warrant further studies. Based on this thesis, even fully remotely sensed forest mapping is already practical with the same accuracy level as traditional SWFI (III). Monitoring forest biomass changes is one of the near-future applications where active RS data will be required. Data acquisition costs are dropping all the time, and data processing is becoming more automated, enabling its use in larger areas, even in global applications.

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