FlexWood

Flexible Wood Supply Chain

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Description of tree and wood resources in the forest based on novel technologies

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SEVENTH FRAMEWORK PROGRAMME

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Table of Contents

Abbreviations

2-D, 3-D	2-Dimensional, 3-Dimensional
AGL	Above Ground Level
ALS	Airborne Laser Scanning
CBH	Crown Base Height
CHM	Canopy Height Model
CIR	Colour Infra-Red
CT	Computer Tomography
DBH	Diameter at Breast Height
DSM	Digital Surface Model
EI	Error Index
FOCC	Forest Owners Consulting Center
LDA	Linear Discriminant Analysis
MSN	Most Similar Neighbour
nDSM	normalized Digital Surface Model
NDVI	Normalized Difference Vegetation Index
RENDVI	Red Edge Normalized Difference Vegetation Index
RF	Random Forest
RMSE	Root Mean Squared Error
SD	Standard Deviation
SVM	Support Vector Machine
TLS	Terrestrial Laser Scanning
VI	Vegetation Index
WP	Work Package

1. Executive Summary

Objectives

The overall objective of the Flexwood project is to build a novel logistic system ('Flexwood') to optimize information flow in the wood supply chain and thus produce more accurate and timely knowledge for decision making. In order to design and implement such a system, novel concepts and measures for information assessment, information flow and the integration of existing technologies and tools are necessary. The basic inputs required by the Flexwood system are the forest information (e.g. tree diameters, species, limited quality information) collected in traditional field inventories. Different remote sensing techniques are correspondingly expected to provide geographically accurate and detailed information on wood qualities and quantities. Within the Flexwood system, the use of advanced sensing technologies is expected to allow a better understanding of the forest resources at lower costs compared to traditional field inventories.

This deliverable reports the work done within Work Package (WP) 4000 (tasks 4100–4300), which developed an integrated forest inventory design for optimized quality and quantity assessment of wood resources. The main objective was to use remote sensing data from both aerial (ALS) and terrestrial (TLS) laser and optical technologies to obtain advanced quality and quantity information on wood resources measured in the forest with the novel technology. The specific research objectives were

- to develop and optimise ALS and TLS methods for assessment of wood quality and quantities at high spatial resolution and validate these methods, and
- to optimise the combination of different data sources, such as ALS, TLS, existing geo-spatial data, optical sensor data and field measurements, in description of tree and wood properties.

WP 4000 produces output to be used by later Flexwood work packages in defining optimisation models for tactical and operational planning (bucking, harvesting, allocation of wood) (WP 5000), and optimisation models and enhanced processes for novel and more flexible concepts for mill production (WP 6000). The measures developed within WP 4000 will be enhanced and tested for their effectiveness and efficiency in the framework of defined use cases (WP 8000).

The approach

The different sensors can be seen as complementary data sources, so that the airborne data provide a wall-to-wall coverage of the study area and TLS data and/or field measurements provide a detailed description of tree quality attributes on a sample basis. The analyses may be performed at the level of individual trees or directly at an aggregated level (e.g. plot / stand) independently on different data sources. Within the Flexwood project there is a particular interest in combining the area-based and tree-level laser scanning approaches in order to derive forest information (both quantity and quality). There is a prior need to develop both ALS and TLS methods with respect to these requirements, including integration with other remote sensing data sources and calibration field measurements, for example.

To achieve these objectives, the work package was structured into three separate components, these being wood resource assessment using airborne data (WP 4100), TLS data analysis for obtaining detailed stem information (WP 4200), and integration of these data sources (WP 4300). The experiments were carried out on four separate test sites located in Germany, Sweden, Norway, and Finland. The test sites had various coverage of field measurements and corresponding remote sensing data, including ALS data, TLS data, and multispectral and hyperspectral image data in varying resolutions.

The work carried out within WP 4100 developed components of single-tree inventory by airborne data. In the method development, a particular focus was set on tree species recognition, which was identified as an important yet challenging attribute to be estimated by means of ALS only. Combinations of ALS and spectral information were tested on several study areas to improve tree species estimates. In addition to tree detection, the validation was performed with respect to species, stem dimensions, and branch height properties. Area-based estimation of biomass, volume and species proportions was carried out, and the area-based technique was used to detect stands with a high economic value.

WP 4200 aimed at accurate measurement of the tree stem characteristics applying TLS data. In the work carried out, a selection of trees was scanned applying TLS prior to cutting. The work developed process steps to gain information about the geometrical parameters (position, dimensions) and bark quality of the trees by TLS data. The measured trees will be later felled and measured by computer tomography for their internal wood properties (WP 6100). Quality information of the felled trees processed by use of the laser data will be linked to quality criteria of computer tomography.

The work of WP 4300 focused on integrating the analysis of TLS-based forest inventories into ALS and/or aerial images based inventories. The method development related to linking ALS and TLS datasets from the same area. A more general aim was to describe a methodology on how to integrate tree and wood properties from different sources to provide sufficient data as input into a novel logistic concept (WP 5000).

Obtained results

A summary of the obtained results is shown below. The figures are best-case accuracies, which vary depending on the properties of the data and the study area. The errors are either classification accuracy or root mean squared error.

A summary of the tree-level accuracies obtained within the study:

Attribute	Test site	Data source	N	Absolute error	Relative error
Species	Sweden	hyperspectral	108	-	21–62 %
	Norway	ALS	1520	-	23–26 %
	Norway	multispectral	1520	-	21–29 %
	Norway	hyperspectral	1122	-	12–16 %
	Norway	ALS + multispectral	1520	-	9–12 %
	Finland	ALS	2985	-	9–12 %
Stem volume	Germany	ALS + multispectral	178	221–525 dm^3	24–57 %
	Finland	ALS	2985	103–148 dm^3	35–51 %
DBH	Germany	TLS	14	0.50 cm	1 %
	Finland	ALS	2985	2.9–3.9 cm	15–30 %
Tree height	Finland	ALS	2985	0.7–1.6 m	4–9 %
Crown base height	Finland	ALS	2067	1.5–1.8 m	15–18 %
Dead branch height	Finland	ALS	2067	2.8–3.7 m	85–112 %

A summary of the plot-level accuracies obtained within the study:

Attribute	Test site	Data source	N	Absolute error	Relative error
Biomass	Germany	ALS	374	54 t/ha	35 %
Proportion of conifer trees	Germany	ALS	374	-	17.5 %
Total volume	Germany	ALS	374	96 m^3/ha	33 %
	Finland	ALS	79	33–38 m^3/ha	17–19 %
Diameter distribution	Finland	ALS	79	EI 832–834	-
Tree detection	Finland	ALS	79	-	44 %
	Germany	TLS	23	-	16 %
Tree position	Germany	ALS		1.6 m	-

The obtained results suggest ALS as a useful data source for estimating attributes for the trees dominating in the forest canopy, and that there are several established techniques for performing the tree-level analysis. The position, height and crown attributes such as width (or diameter or area), volume and length are produced for each detected tree. The accuracies of these estimates vary, not all trees can be detected and the estimates are prone to systematic errors. Further attributes are estimated by including local field reference data in area-based or tree-level imputation. Notably, species-specific attributes and diameter distributions were predicted based solely on ALS data, but the species-specific prediction was improved by integrating ALS with optical data from multispectral or hyperspectral images. Besides estimation, the area-based technique was found useful for detecting stands with a high economic value.

TLS was found to be an effective sample-based measurement technique, enabling DBH measurements with an accuracy comparable to manually performed calliper measurements, and a potential source for bark characterization. However, these results were based on only 14 trees scanned from multiple directions, while an automated analysis of the single-scan TLS data showed less accurate results. Not all trees could be detected and the analysis showed a tendency to underestimate the DBH. The probability of tree detection decreased with an increasing distance to the scan centre. Thus, further developments are needed to optimize the integrated use of TLS data with airborne data sources. In addition to the obtained results, promising research areas and techniques that need further verification are identified.

2. Introduction

The overall objective of the Flexwood project is to build a novel logistic system ('Flexwood'). The project will develop supply chain optimisation models at both a tactical and strategic planning level, which will support decision-making towards matching the wood supply from the standing forest with competing industry requirement. The basic inputs for the modelling concepts are the different types of information gathered from the forest. In order to design and implement such a system, novel concepts and measures for information assessment, information flow and the integration of existing technologies and tools are necessary.

The forest data requirements of many FlexWood components comprise that properties estimated with several data sources are integrated into a common database. In a cut-to-length system the FlexWood concept requires tree and forest data to simulate the product recovery from the bucking process in a harvester. Today bucking simulation is based on stand inventory data which include average DBH, species distribution, stem volume and total stand area. External properties of each tree are given from typical trees in terms of damage, quality classes and diameter distributions. The lack of accurate measurement data commonly leads to an inaccurate forecast of product recovery regarding total volume, species distribution, log diameters and length distributions, but also frequency of downgraded logs and distribution into quality classes.

During the last years, the development of various sensing techniques has made it possible to provide more accurate tree and forest data, and also with better resolution than previous field based inventories. Laser techniques, such as airborne laser scanning (ALS) and terrestrial laser scanning (TLS) are identified as the most promising technologies to provide timely, geographically accurate, and detailed information on wood qualities as well as quantities. ALS improves the tree size distribution at stand level while TLS provide information on the tree stem properties. However, to reach the demand of forest information in novel logistic concepts other source of information must be added to the forest description. Better input data also give opportunities to optimize the choice of stands in order to meet the industry supply demand in a more precise way.

2.1 Objectives of the Deliverable

The main objective of this deliverable is to use remote sensing data from both aerial and terrestrial laser and optical technologies to obtain advanced quality and quantity information on wood resources measured in the forest with the novel technology. The forest information will be based on an integrated system of ALS and TLS data combined with existing data sets and derived measurements. This will provide the necessary information for the various supply chain models (harvesting, allocation, logistics, transportation) such as digital terrain models, stand descriptions, wood quantity dimension and assortment alternatives and wood quality.

The specific research objectives are

- to develop and optimise ALS and TLS methods for assessment of wood quality and quantities at high spatial resolution and validate these methods, and
- to optimise the combination of different data sources, such as ALS, TLS, existing geo-spatial data, optical sensor data and field measurements, in description of tree and wood properties.

2.2 Work Package Task Status

The work package (WP) 4000 *"Integrated Forest Inventory Design for Optimised Quality and Quantity Assessment of Wood Resources"* is structured into the following tasks:

Task 4100: Mapping and modelling of wood resources using remote sensing tools and existing geo-spatial data
Task 4100 focused especially on airborne assessment of the wood resources. The aim was to develop components of the synergetic use of ALS and spectral image data, e.g. digital aerial photographs, for single tree and area based inventory including species information. It involved modelling multivariate response (e.g. diameter, height and quality by tree species) applying non-parametric for linking terrestrial and remote sensing data. A special attention was given to tree quality parameters.

Task 4200: Mapping and modelling of wood resources and quality integrating terrestrial sensor techniques
Task 4200 developed TLS techniques for a detailed analysis of the tree quality parameters. The work developed process steps to gain information about the geometrical parameters (position, dimensions) and bark quality of the trees by TLS data. Furthermore, it involved identification of irregularities (e.g. scars of the bark) and linking this information to the internal quality of the stems, assessed later (WP 6100) by computer tomography. Two specific topics of this task, namely "Acquisition of species information from the point cloud" and "Branch detection" are not considered in this deliverable.

Task 4300: Integrated concepts for description of tree and wood properties in the forest
Task 4300 focused on integration of aerial and terrestrial data on sample plots by field measurements and TLS. It involved linking trees detected from the TLS data to field measurements, and further linking of these data sources to the ALS data. This task combined the knowledge obtained in previous tasks 4100 and 4200 towards an information system to be validated later (WP 8000).

Task 4400: Interface and operative tools to connect standing tree and wood properties to novel logistic concepts
Task 4400 aimed at software development to compile all the measurement and stakeholder information into one information system. The work involved an identification and implementation of measurement formats (connected to WP 7000) and interfaces and operative tools connecting into the FlexWood model system (WP 5000).

This deliverable 4.1 describes the work carried out within tasks 4100–4300. The work carried out in 4400 will be reported in another deliverable (Table 2.2.1). This deliverable constitutes Milestone 2 of the Flexwood project, WP 4000 being involved also in two later milestones (Table 2.2.2).

Table 2.2.1 Deliverables of WP 4000.

Del. no.	Deliverable name	Delivery date	Status (pending/submitted/ accepted)
4.1	Description of tree and wood resources in the forest based on novel technologies	Month 24	
4.2	Interface and operative tools to connect standing tree and wood properties to novel logistic concepts	Month 26	

Table 2.2.2 Project milestones where WP 4000 is involved.

Milestone number	Milestone name	Work packages involved	Expected date	Means of verification	Status
2	Description of tree and wood resources in the forest based on novel technologies	4000	Month 24	Deliverable 4.1 validated by SME and industry partners	
3	Novel logistic concept integrating forestry with industry	3000 4000 5000 6000 7000	Month 27	Deliverable 5.4 validated against identified improvement needs and by SME and industrial partners	
4	Software for increased wood supply efficiency	4000 5000 6000 7000	Month 28	Deliverable 7.3 software released and tested within the use cases deliverable 8.1	

2.3 Links to other Flexwood work packages

WP 4000 is related to other Flexwood work packages as described in the following. The output produced by WP 3000, which described the demands of main industrial sectors within the wood supply chain in terms of wood raw material qualities, were used in WP 4000 when refining the relevant forest attributes to be extracted from the remote sensing data sets. The estimation accuracies of these attributes were compared with the industrial requirements in the summary part (Section 8) of this deliverable.

The output produced by WP 4000 will be used in optimisation models for tactical and operational planning (bucking, harvesting, allocation of wood) (WP 5000), and optimisation models and enhanced processes for novel and more flexible concepts for mill production (WP 6000). The measures developed within WP 4000 will be enhanced and tested for their effectiveness and efficiency in the framework of defined use cases (WP8000). The task 8200 will assess the sustainability performance of the FlexWood concept on the wood supply chain through a cost-benefit analysis.

3. The Approach

3.1 The rationale

The basic inputs for the modelling concepts within Flexwood (WPs 5000, 6000) are the forest information collected in traditional field inventories. Forests are usually characterised by registering species and measuring tree diameters and heights in the field. Measurements on the external quality of trees, such as branch height or curvature are taken only from sample trees, since these measurements are found to be too laborious in practice. In this way actual saw log recovery, i.e. saw log recovery in the light of technical defects and bucking constraints, can be measured or assessed, yet this information is rarely collected.

During the recent years, airborne laser scanning (ALS) and terrestrial laser scanning (TLS) have been identified as the most promising technologies to provide geographically accurate and detailed information on wood qualities as well as quantities at low costs, in order to allow a better understanding of the forest resources. Both techniques are non-destructive and non-touching, and thus do not require that the tree is harvested to get sufficiently accurate information. ALS data have been used for many forestry purposes in recent years, including the prediction of mean stand characteristics, pre-harvest inventories, comparisons of forest inventories based on cost plus loss analysis, ecological studies and assessments of forest growth issues, to name but a few (Næsset 2007, Peuhkurinen et al. 2007, Eid et al. 2004, Pesonen et al. 2008, Yu et al. 2004).

The use of ALS data can provide certain tree or stand quality characteristics, such as branch height properties (Maltamo et al. 2009b, Bollandsås et al. 2011). However, more detailed analysis of tree quality attributes can be made with the help of terrestrial laser scanners or field measurements. Especially for the processing of the stem in the saw mill additional information about the internal quality of the tree is indispensable. It can be predicted by observation of the outside of the stem by connecting the automatic detection of patterns in the recorded exterior view of a standing tree with irregularities in the inside.

Within the Flexwood project there is a particular interest in combining the two basic laser scanning approaches in order to derive forest information (both quantity and quality) at the tree level. There is a prior need to develop both ALS and TLS methods with respect to these requirements, including integration with other remote sensing data sources and calibration field measurements, for example. A particular focus is set on validating the estimation accuracies of the key forest attributes for forest industry, as identified by WP 3000, at various test sites located in Europe.

The following sections detail the research objectives considered in this deliverable, regarding wood resource assessment using airborne data (WP 4100 – section 3.1.1), TLS data analysis for obtaining detailed stem information (WP 4200 – section 3.1.2), and integration of these data sources (WP 4300 – section 3.1.3). The datasets and the methodology are described in detail in sections 4–7, and the summary of estimating the key attributes is given in section 8.

3.1.1 Wood quantity and quality assessment by airborne data

In general, ALS data can be applied on an area or individual tree basis (e.g. Næsset et al. 2004, Hyyppä et al. 2008, McRoberts et al. 2010). The major difference between these approaches is that the latter relies on the segmentation of the individual trees, whereas the former uses height hits directly at the plot (or grid cell or stand) level to estimate forest characteristics by means of regression analysis or nearest neighbour methods. In the latter case, these characteristics are model based estimates, i.e. they are not based on actual trees of a stand. Therefore, a single-tree approach enabling direct measurements of position, height and crown shape of the trees dominating in the canopy layer may be better suited for a detailed forest inventory including tree quality attributes.

Remote sensing data provide certain attributes, such as tree height, that can be directly evaluated for measurement accuracy. From a statistical point of view, however, the data are mainly auxiliary variables that can be used in the process of up-scaling the information from initial computation units (trees / sample plots) to a larger, but still spatially explicit area. To model the multivariate response (e.g. diameter, height and quality by tree species), non-parametric methods such as Most Similar Neighbour (Moeur and Stage 1995) or Random Forests (Breiman 2001) are used for linking terrestrial and remote sensing data. There are promising results on predicting species (Ørka et al. 2009a; Korpela et al. 2010), quality attributes (Maltamo et al. 2009b) and all tree attributes simultaneously (Vauhkonen et al. 2010) using various non-parametric methods, but these are typically carried out using limited datasets, and thus further verifications are needed.

The assessment of tree species forms as a particular challenge (e.g. Barth et al. 2008), where ALS data has been recognized as a less than optimal technique especially in distinguishing deciduous tree species from the coniferous (e.g. Korpela et al. 2010). Therefore a combination of spectral images with ALS data is tested. The idea is to combine vegetation height information from ALS with various passive airborne systems that provide high resolution radiometric data.

The work carried out within WP 4100 developed components of single-tree inventory by airborne data. Combinations of ALS and spectral information were tested on several study areas to improve tree species estimates. In addition to tree detection, the validation was performed with respect to species, stem dimensions, and branch height properties. Area-based estimation of biomass, volume and species proportions was carried out, and the area-based technique was used to detect stands with a high economic value.

3.1.2 Quality parameters gained by terrestrial laser scan data

By use of TLS data, a very accurate measurement of the tree stem is possible, but it may cover only one side of the stem if only a single scan is performed. Thus two-dimensional information may be deduced, corresponding to a diameter measurement performed with a calliper from only one direction. More adapted measurements to the three dimensional shape of the stem require that the TLS data are acquired from different positions around the tree. In that case, consecutive cylinders fitted to the point cloud data represent the shape of the stem, and attributes such as position, average diameter at different heights, taper and sweep may be extracted.

Additional to the stem parameters the height of the branches, branch diameters and the height to the crown base can be measured. As not only the three dimensional position of each point gathered by the scanner is detected and processed but also the intensity of the beam, these intensity data can be analyzed. Here, bark characteristics can be identified and then measured by use of the three-dimensional information. The exterior quality can be used to deduce information about the interior of the stem.

In WP 4200, the trees were scanned applying TLS prior to cutting. Afterwards they are felled and the trees will be measured by a computer tomography for their internal wood properties (WP 6100). Quality information of the felled trees processed by use of the laser data will be linked to quality criteria of computer tomography.

3.1.3 Integration of aerial and terrestrial data sources

Remote sensing data always need field measurement to find relationship between imagery and field attributes. However, the role of the field measurements is not just to act as ground truth in training and validation data purposes. After model construction field data can be used to calibrate estimates for smaller areas. This can be very effective alternative if advanced statistical modelling techniques are applied (e.g. Siipilehto 2006).

The role of the TLS data can be independent, very detailed and even tree level data source. This kind of data is of specific use, for example, in pre-harvest inventories dealing with rather small areas. However, more effective results might be obtained if TLS is combined with ALS. Whereas ALS usually provides 100% wall-to-wall coverage of the inventory area, TLS is collected just from some sampling points. The integration of these data sets can be done at stand, plot or tree level. In this case a considerable amount of quality related information can be linked to ALS data. However, especially at tree level linkage of ALS and TLS detected trees still needs method development.

The benefits of integration of optical imageries and ALS are primarily related to tree species recognition which can be improved by using e.g. hyperspectral or multispectral data. This will improve especially the separation between coniferous and deciduous tree species. Also in the combination of optical imageries and ALS ground truth data are needed for model learning. The role of the optical imageries can also be to generalise ALS and field information to considerable larger areas which are only partly covered by ALS. This sampling based use of ALS is, however, not the aim of this project.

All these integration purposes need for statistical methods such as non-parametric nearest neighbour imputation or mixed-effects modelling. As a result optimal combination in each situation can be found.

The work of WP 4300 focused on integrating the analysis of TLS-based forest inventories into ALS and/or aerial images based inventories. The method development related to linking ALS and TLS datasets from the same area. A more general aim was to describe a methodology on how to integrate tree and wood properties from different sources to provide sufficient data as input into a novel logistic concept (WP 5000). The described methodology has been the basis for implementation of the FlexWood concept applied into the Northern European use case and will be evaluated within WP 8000.

3.2 Evaluation criteria and performance measures

In case of variables with a continuous scale, the correspondence of the estimates with the reference data was typically evaluated in terms of root mean squared error (RMSE) and bias:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{n}} \quad \text{and} \qquad (1)$$

$$bias = \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)}{n}, \qquad (2)$$

where *n* is the number of observations, and y_i and $\hat{y}_i$ are the reference and estimated attributes, respectively. The relative RMSEs were calculated by dividing the absolute RMSE values by the mean of the reference attribute. In case of nearest neighbour estimation, this measure is sometimes referred as root means square distance (RMSD), which is comparable to the RMSE of parametric models (Crookston & Finley 2008).

In case of categorical variables, the accuracy indices used were the proportion of correctly classified trees for single species (producer's accuracy), the total (overall accuracy) and the kappa coefficient (κ) (Cohen, 1960; Story & Congalton, 1986).

4. Study areas and data sets

4.1 Germany (FELIS, IWW, FVA, Treemetrics)

The German study area is lying in the Rhine-valley in south-west Germany near to the town Karlsruhe. The area covers about 10 km² and is stocked with beech (*Fagus sylvatica* L.), pine (*Pinus sylvestris*) and oak (*Quercus petraea* and *Quercus rubra*) as dominant tree species. The vegetation height reaches up to 40 m. The terrain is plain and situated in 101–123 m height above sea level. A detailed description of the area is given by Straub and Koch (2011). In summer 2008 a flight campaign was arranged. Table 4.1.1 shows the parameters of the used multispectral digital line camera from TopoSys (Falcon II system). Toposys delivered, based on these digital image information, a true-orthophoto of the whole test site with four channels (blue, green, red, Near infra-red).

Table 4.1.1 Parameters of the flight campaign in summer 2008 using a multispectral line scanner integrated in the "Falcon II system" (AGL = above ground level).

Parameter	Value
Flying height AGL [m]	700
Spectral channels [nm]	Blue: 450–490 Green: 500–580 Red: 580–660 Near infrared: 770–890
Viewing angle [°]	21.6
Pixels per line	682
Ground sampling distance [m]	0.4

The Full-waveform laser scanner data were acquired at the end of November 2009 by Milan Geoservice GmbH using the IGI Litemapper 5600 system with a Riegl LMS-Q560 (240 kHz) scanner. A high point density (> 20 rays/m^2) was obtained as the study area was flown twice, in north-south and in east-west direction. The flight and system parameters are shown in Table 4.1.2.

The full-waveform data was processed using the software "RiANALYZE 560" and was delivered in ASCII format with 3D coordinates of the reflections and additional information such as target number, number of targets in beam, echo signal amplitude, the echo pulse width and distance corrected intensity values.

Additionally data from a flight campaign in winter 2009 were used by FVA. The data were acquired by the state survey institute on January 31 – February 3, 2009, with the properties given in Table 4.1.3.

Table 4.1.2 Flight and system parameters of the flight campaign in summer 2009 with the "Harrier 56" LiDAR system.

Parameter	Value
Measurement rate [kHz]	240
Field of view [°]	60
Flying height AGL [m]	600
Flying speed [m/s]	46
Density [points/sqm]	22
Vert./horiz. accuracy (excl. GPS errors) [m]*	~0.1/~0.03

Table 4.1.3 Flight and system parameters of the flight campaign in winter 2009

Parameter	Value
Measurement rate [kHz]	100
Scan frequency [Hz]	47
Field of view [°]	+- 18
Flying height AGL [m]	800
Flying speed [km/h]	167
Strip width [m]	490
Density [points/sqm]	20

Measurements for reference field data of inventory plots at Karlsruhe test site were also conducted. Furthermore preparation work were done for all 40 inventory plots measured later by Treemetrics using a TLS system (2 days with 3 persons). Support of Treemetrics doing the TLS measurement for one week two persons were involved. In a post processing step adjustment and correction of the point clouds delivered by TreeMetrics were made. This included software development and data preparation. In a last step the development (programming work) of a stem file parser, which can read the data delivered by TreeMetrics as input data, was realized. The parser creates stem lists including the x,y,z coordinates, the breast height diameter (dbh) and the stem volume in such formats, that the data is than compatible to standard statistical and geo-processing tools used in this project.

Additionally, Albert-Ludwigs-University Freiburg, Institute for Forest Growth (IWW) acquired terrestrial laser scanning data in February 2011. Altogether 14 trees were scanned in multi-scan mode with Z+F IMAGER 5006.

4.2 Sweden (FORAN, Skogforsk)

The data used for the investigation and method is taken from the data set used in the Northern Europe use case in the Flexwood project work package WP 8000 – implementation and demonstration of the flexwood project. The forest area used for the WP 8000 use case is located 100km north of Stockholm, Sweden (lat. 60°12´N, long. 18°00´E). The total area is approximately 16 00ha and consists of managed boreal forest dominated by Scots pine (*Pinus sylvestris*) and Norway spruce (*Picea abies*). There are also some deciduous trees, mainly birch. For this study only a subset of the total area was used. Laser data and hyperspectral data was acquired simultaneously on September 30 and October 1 2010 by the Latvian operator Forest Owners Consulting Center" (FOCC) (www.mikc.lv). (Tables 4.2.1 and 4.2.2).

Table 4.2.1 Flight and system parameters of the ALS flight campaign in Autumn 2010 with the Optech ALTM Gemini LiDAR system. The first, last and intermediate laser returns were recorded.

Parameter	Value
Measurement rate [kHz]	125
Field of view [°]	+-11
Flying height above AGL [m]	700
Density [points/sqm]	9

Table 4.2.2 The spectral bands of ITRES CASI-1500 hyper spectral image.

Band no.	Centre wavelength [nm]	Half band width [nm]
1	427.3	28.6
2	479.8	23.9
3	518.0	14.3
4	551.4	19.1
5	597.9	27.5
6	633.7	8.4
7	671.9	29.8
8	710.1	8.4
9	728.0	9.5
10	742.3	4.8
11	761.4	14.3
12	836.6	60.8
13	934.3	37.0

The hyperspectral images were acquired using the ITRES CASI-1500 hyper spectral image scanner (www.itres.com). The scanner was set to collect 13 spectral bands of different width from 398.7 nm to 971.3 nm. The average pixel size on the ground was 0.35 m. The collected image data was post processed by FOCC and orthophoto images was produced using a canopy surface model based on laser data.

A subset of 8 field plots (circular 8 m radius) was selected and used for this study. The dominating trees in these plots where used for training the classification, in total 30 spruces, 36 pines and 5 broadleaf trees. For the evaluation additional field data was collected.

For evaluation of the classification two additional areas, or “plots”, where used, one dense forest area with all species represented and one sparse forest area dominated with pine. The number of trees in each area was approximately 50. The field data was collected after the single trees were identified using the ALS data and the species information was noted for each identified tree.

4.3 Norway (UMB)

The study area is located in the municipality of Aurskog-Høland, in southeast Norway (59°50′N, 11°34′E, 120–390 m a.s.l.). The forest is dominated by Norway spruce (*Picea abies*) and Scotch pine (*Pinus sylvestris*). The most common deciduous tree species are birch species (*Betula* spp.) and trembling aspen (*Populus tremula*).

The remote sensing data include three different sources, i.e. 1) ALS, 2) multispectral and 3) hyperspectral images:

1. Two ALS datasets were acquired with Optech ALTM 3100 on 12 June 2006 with pulse density 7.4 points/m^2 and with Optech ALTM Gemini on 12 May 2009 including pulse density 6 points/m^2.

2. Two different datasets of multispectral imagery were used. The first dataset was acquired 28–29 June 2005 using a Vexcel aerial camera. The pixel size on the ground was 27.5 cm. The second aerial photograph dataset was acquired 12 June 2006 using an Applanix aerial camera. The pixel size on the ground was about 12 cm.

3. The hyper spectral data were obtained in 27 August 2008. The hyperspectral sensors Hyspex Swir-320i and Hyspex VNIR-1600 were used. The hyperspectral images cover consists of 307 bands of different widths from 0.4–1.7 µm. A description of the properties of these sensors can be found at: http://www.neo.no/products/hyperspectral.html#products. The hyperspectral images were orthorectified, using a Digital Terrain Model. The pixel size for the the final orthorectifed images were 40 cm and 150 cm for the VNIR and SWIR data, respectively.

Field work was carried out in the dormant season of 2007–2008, i.e., 15 October 2007 to 14 April 2008. In total 40 field plots with a size of 500–1000 m^2 were inventoried. This data includes tree-level measurements with positioned trees.

4.4 Finland (UEF)

The study area is a typical boreal managed forest area in Kiihtelysvaara in eastern Finland. Scots pine (*Pinus sylvestris* L.) is the dominant tree species. It represents 73% of the volume, Norway spruce (*Picea abies* [L.] Karst.) 16% of the volume and deciduous trees altogether 11% of the volume.

High resolution ALS data were collected on June 26, 2009 using an Optech ALTM Gemini laser scanning system (Table 4.4.1). Each location was covered from two flight lines (side overlap 55%) in order to maximize the probability that trees have ALS hits each side, i.e. that there are no shadowed areas behind trees along the line from the laser scanner to a tree. The intensity data were range-corrected by the data deliverer.

Table 4.4.1 Flight and system parameters of the flight campaign in summer 2009 with the Optech ALTM Gemini laser scanning system.

Parameter	Value
Measurement rate [kHz]	125
Field of view [°]	26
Flying height above AGL [m]	600
Density [points/sqm]	12

The field measurements were carried out on May-June, 2010. Altogether 79 field plots were placed subjectively, attempting to record the species and size variation over the area. Sample plot size varied between 20x20 and 30x30 meters according to stand development class (see more details in Packalén et al. 2011 and Vauhkonen et al. 2011).

The high resolution ALS data were employed in the mapping of the trees. First, a tree map was produced using the individual tree detection method. The tree locations were verified in the field and the undetected trees were positioned using angle and distance observations to the ALS-detected trees. The coordinates for the small trees were then calculated using these observations in a least squares adjustment. All trees with either DBH ≥ 4 cm or height ≥ 4 m were mapped.

5. Mapping and modelling of wood resources using remote sensing tools and existing geo-spatial data

5.1 Methods

5.1.1 Tree-level and area-based inventory (Central Europe Use Case – FeLis, FVA)

Two single tree detection algorithms were enhanced, extended and finally applied to the Karlsruhe test site area. Furthermore a new stem fitting algorithm was developed based on ALS data. For this algorithm no final accuracy check could be done within the given time schedule, but preliminary results are given. Alternatively, the terrestrial inventory data were linked with ALS data by nonparametric, area-based methods. Volume, biomass and proportion of deciduous / coniferous trees were calculated for 452 m^2 hexagons to be used in later WPs (5300, 8000). Here the information is aggregated to forest stands.

The first method performs single tree delineation and tree stem volume estimation using colour infra-red (CIR) images and ALS data (Straub & Koch 2011). The basic tree delineation method is mainly based on a pouring algorithm (Koch et al. 2006; Weinacker et al. 2004). It was extended by introducing a pre-processing step using CIR data or in case that the ALS data are captured during leave off time, by using two DSMs calculated once based on the last pulse and a second one calculated using only first pulse data. Introducing this pre-processing step, it is possible to classify the forest area into the two classes of coniferous and broadleaved forest. Using this knowledge, especially coniferous and young broadleaved trees or vice versa, which have been interleaved, can be separated. The pouring algorithm will stop growing a region, when it reaches the boarder-line of a tree belonging to the other class. This means that the pouring algorithm has to be executed twice. After tree delineation, tree height, crown diameter and crown volume were estimated. Based on these parameters, several methods were introduced and tested to estimate the stem volume of pine trees. All the regression methods are shown in Table 5.1.1. Both tree delineation and stem volume estimation are described in full detail by Straub and Koch (2011).

Table 5.1.1 Allometric models for stem volume estimation. The input parameters are tree height (*h*), crown diameter (*cd*) and crown volume (*cv*). The regression parameters are β_0, β_1, β_2 and β_3. The stem volume, which will be modelled, is *v*.

No.	Model
1.	$\log(v) = \log(\beta_0) + \beta_1 \log(h)$
2.	$\log(v) = \log(\beta_0) + \beta_1 \log(cd)$
3.	$\log(v) = \log(\beta_0) + \beta_1 \log(cv)$
4.	$\log(v) = \log(\beta_0) + \beta_1 \log(h) + \beta_1 \log(cd)$
5.	$\log(v) = \log(\beta_0) + \beta_1 \log(h) + \beta_1 \log(cv)$
6.	$\log(v) = \log(\beta_0) + \beta_1 \log(cd) + \beta_1 \log(cv)$
7.	$\log(v) = \log(\beta_0) + \beta_1 \log(h) + \beta_1 \log(cd) + \beta_2 \log(cv)$

The second tree detection method was based on supervised k-means algorithm (Gupta et al. 2010). Data processing was carried out on 77 plots, each of size 300 by 400 m. Local maxima above 4 m height were calculated using normalized digital surface model (nDSM) having a gray value larger than the gray value of all its eight neighbouring pixels. Next, the superfluous local maxima detected from the multiple peaks from the crown were excluded using a search algorithm implying a threshold distance criteria. The distance between the two points is computed in Euclidean 3-D space. If the distance between the two points is less than the threshold distance defined, then the point selected is removed. This process is continued until all the local maxima points below the threshold distance are removed. The supervised k-means algorithm with local maxima as external seed points was ran over ALS point cloud to generate single tree clusters. The supervised k-means has two major advantages over traditional approaches: first, random seed selection procedure with a trial and error based approach containing several repetitions to select an appropriate k clusters can be completely avoided and second, reduction in the time and machine cost. The tree clusters containing 3-D information (tree top position and tree height) of each ALS point were used to derive other tree parameters. The results were validated using 2-D distance matching criteria between the reference and detected tree top points in the 26 plots.

The area-based approach used ALS-data from 2009 with up to 20 points per m². The data were pre-processed by the state survey service. During pre-processing each laser point was classified in one of four classes (Schleyer 2001): (i) vegetation first pulse; (ii) vegetation last pulse; (iii) ground first pulse; or (iv) ground last pulse. If a laser beam resulted in only one hit, it was classified as both first and last pulse. Data of the terrestrial forest inventory of 2006 were used as reference. The inventory follows a standard procedure of the forest service Baden-Württemberg, i.e. a raster inventory with 12 m concentric plots in 200 x 100m sample grid (Kändler & Bösch 2002). The following variables were calculated for every reference plot:

- Volume per hectare [m³/ha], which describes the wood volume above 7 cm diameter;
- Biomass per hectare [t/ha], which is the total biomass above ground in tons per hectare; and
- Proportion of coniferous wood volume in percent [%].

Because of 3 years difference between terrestrial inventory and the ALS flight, all plots with where harvesting had occurred within this time were excluded from the reference data set. To define those areas, an additional ALS data from 2007 were used. The height difference of the nDSMs calculated with Fusion 2.9 (McGaughey 2010) from both data sets was analyzed. All plots where an area larger than 20 percent had a height reduction more than 2 m were excluded from reference data. Additionally, only those plots which were completely within a single stand were used. The resulting number of plots used for model calibration was 374. The predictions were limited to the productive forest areas of the use case “Karlsruhe”, which were extracted from the existing forest geographic information system (FOGIS). The estimated volume, biomass and proportion of coniferous wood were aggregated to stands as defined by forest management planning.

In the estimation, height and density metrics from ALS data were used as prediction variables. The height metrics were calculated with Fusion 2.9 (McGaughey 2010). The density metrics were calculated as described by Næsset (2002). We assumed that the response is influenced by the combination of different ALS-point classes, and different response variables are calculated with different predictor variables. Therefore all cloud and density metrics were calculated with following different point class combination: (i) separately for all four ALS-point classes; (ii) for all ALS-points together; (iii) for a combination of two point classes, which means: (a) all last-pulse, (b) all first-pulse, (c) all vegetation, and (d) all ground points.

The following nonparametric prediction methods were tested: Most similar neighbour (MSN), most similar neighbour with variance weighting (MSN2) and Random Forests (RF), all being implemented in the R package yaImpute (Crookston & Finley 2008). The model quality was analysed by a 5% leave out cross validation with 30 runs. The error for nearest neighbour models is normally described as root means square distance (RMSD) which is comparable to the RMSE of parametric models. The best model was defined by the lowest mean RMSD of these 30 runs.

5.1.2 Tree species classification based on synergetic use of ALS and hyper spectral image data (FORAN)

The overall method can be outlined as follows. First, the single trees are identified and the tree crowns are delineated using ALS data. Second, the delineation result is combined with hyper spectral image data and used to guide the extraction of spectral responses for each tree crown. Using this information a number of feature parameters is derived for each tree. Third, the parameters associated with the trees in the sample plots are linked with the field data, i.e. ground truth species information, to train a maximum likelihood classifier. Finally, the classification is performed for all trees in the study area and the result is evaluated.

In this study the classification of single trees is based on the spectral response from each individual tree crown. In order to identify the tree crowns, extract the spectral response and perform the classification, a method based on synergetic use of airborne laser scanner (ALS) and hyper spectral image data is employed. FORAN has developed an effective method for identification the single trees based on ALS data, which is routinely used for forest mapping and inventory. The input is ALS data and the output is identified single trees in terms of tree locations, delineated tree crown segments and measured attributes for each tree, e.g. tree height and crown area. The tree crown segments, a.k.a. the crown mask can be applied to image data and support the extraction of spectral information and determination of feature parameters for each individual tree crown. It is crucial that the hyper spectral image data of the tree canopy match the ALS data on a single tree level. To assure this the pre-processing (orthorectification) of the hyper spectral line scanner data is performed using ALS-based canopy height model.

Two established vegetation indices (VI), the Normalized Difference Vegetation Index (NDVI) and the Red Edge Normalized Difference Vegetation Index (RENDVI) were evaluated as feature parameters for the species classification of the single trees. These particular VIs have been selected since they are simple and straightforward and well studied in the literature. They are also ratio parameters known to reduce many forms of multiplicative noise in the images like sun illumination differences, clouded shadows, etc., which is expected to be involved in commercial inventory projects.

The NDVI is defined as a normalized ratio between the reflected radiation in the highest absorption region (red) and highest reflectance region (near-infrared). Thus,

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}.$$

The ρ_{nir} and ρ_{red} are usually determined using the spectral response values from two broad bands. In this work the available bands closest to the bottom of the chlorophyll abortion, approx. 680 nm, and the top of the near infrared high reflectance, approx. 800 nm, were used.

The RENDVI is a modification of the NDVI intended for very high spectral resolution reflectance data. It is defined for two bands along the red edge:

$$RENDVI = \frac{\rho_{(750\,nm)} - \rho_{(705nm)}}{\rho_{(750nm)} + \rho_{(705nm)}}$$

The $\rho_{(x\ nm)}$ is the spectral response value from the band centred at the wavelength x nm. In cases one or both of the bands do not exist the band at the closest wavelength has been used. An example of the NDVI and RENDVI is shown in Figure 5.1.1.

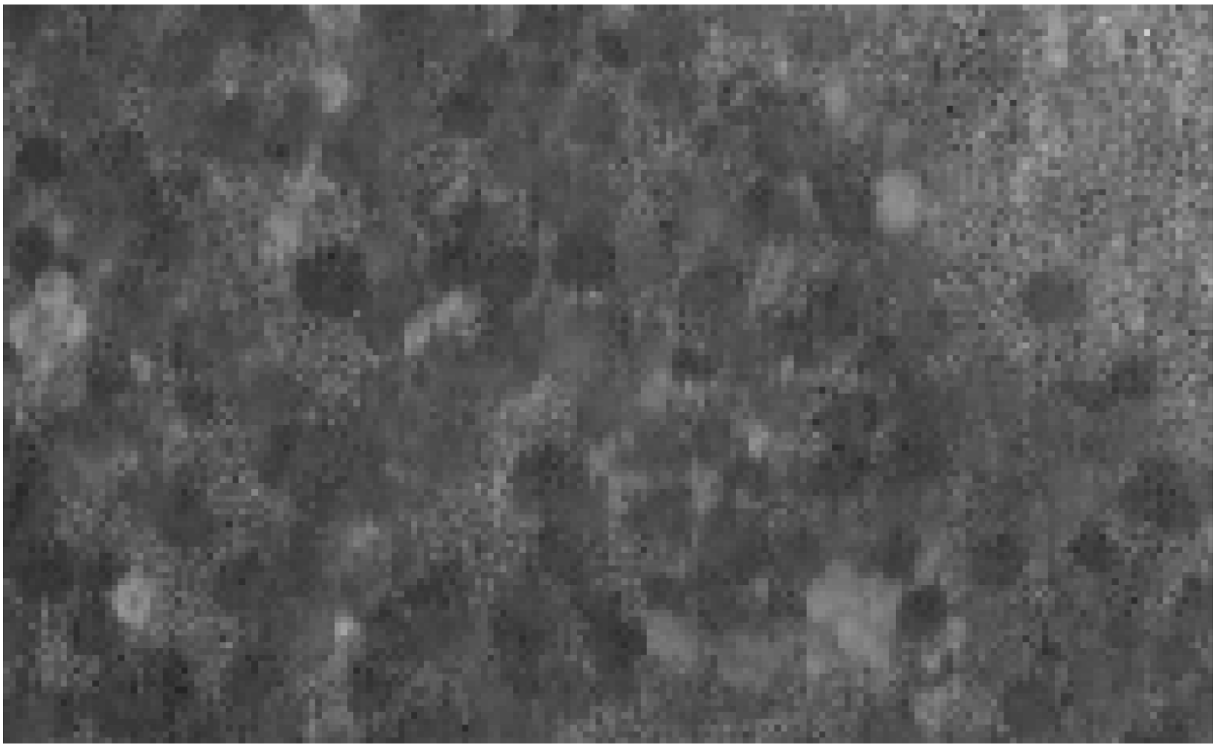


Figure 5.1.1 An example NDVI image of the sample area. The values have been computed for all pixels regardless of the pixel content; tree, ground etc. Among the 13 bands, band 11 (761.4 nm) and band 8 (710.1 nm) has been selected as the input bands. For illustration purposes, the grey scale values in have been inverted in the image.

A reliable linking of field trees and corresponding single trees identified using ALS data is required for a good classification. The linking between the field trees and the single trees was done manually for the 8 plots used in this study. A tree candidate (ALS) closest to a field tree were linked together. In total 71 trees were linked, being 30 spruces, 36 pines and 5 deciduous trees. The NDVI and RENDVI were computed for each linked tree using the image pixels inside the tree crown segments in the crown mask. The NDVI was computed using hyper spectral bands 7 and 12 and wavelengths (centre) 672 and 837, while the corresponding values for the RENDVI computation were 8 and 11 and 710 and 761, respectively. For the classification of tree species, a classifier is trained using field-observed species and VIs for the corresponding trees. A maximum likelihood classifier was used in this study. Finally, the species are predicted for the unknown observations using the classifier.

A special field data collection was done for evaluation of the classification. Two different areas were selected and species was registered for approximately 50 identified trees. The first area was dense and had all species represented. The second area was quite spare and was dominated with pines.

5.1.3 Tree species recognition using ALS and spectral image data (UMB)

The classification accuracy of ALS and multispectral datasets were assessed on 40 field plots. Individual tree crown delineation was performed using an adaptive segmentation method based on a Poisson forest stand model (Ene et al., in press). The algorithm utilizes the average stem density per plot for optimizing the canopy height model smoothing. The stem density was obtained using the area-based approach (Næsset, 2004) and trees were assumed to be randomly located within plots. Furthermore, the tree crowns were extracted using a marker-based watershed algorithm. In total 1520 segments containing one or more trees of the same species were used in the classification of ALS and multispectral data (52% spruce segments, 40% pine segments, and 8% deciduous segments).

From ALS data different height-, density-, and intensity-features were derived according to Næsset (2004) and Ørka et al. (2009a) for all segments. Intensity features were derived from both raw and range normalized intensity. Range normalization was carried out according to Ahokas et al. (2006). The multispectral imagery used consisted of Applanix DSS images acquired simultaneously as the ALS-data and Vexcel Ultracam D images acquired on a separate flight mission. The imagery information was fused with ALS data by a back-projected ALS method. The back-projected ALS method has been reported to be more accurate than using standard orthoimagery based on a digital surface model (Valbuena et al., 2011). Three dimensional ALS metrics, intensity and image metrics were derived for each tree segment. However, the image metrics were computed for relative band values and as ratios (c.f. Breidenbach et al., 2010; Packalén et al., 2009).

Feature or variable selection was based on the analysis of group differences which are common in individual tree classification studies (Brandtberg, 2007; Holmgren & Persson, 2004; Ørka et al., 2009a). We used a similar approach utilizing analysis of variance (ANOVA) and correlation analysis. Classification of ALS and multispectral data were carried out with linear discriminant analysis (LDA), random forest (RF) classification, and support vector machines (SVM). LDA is the most frequently used method in individual tree classification studies. We used the LDA implementation in the R-package MASS for the classification (Venables & Ripley, 2002). RF is an extension of classification and regression trees (Breiman, 2001). RF has shown good results in comparative classification studies on individual trees (Korpela et al., 2010; Ørka et al., 2009b). RF classification was conducted using the R-package randomForest (Liaw & Wiener, 2002). SVM has not been extensively used in individual tree species classification. However, the benchmark which RF is compared against is often SVM (Liaw & Wiener, 2002; Pal, 2005). SVM classification was conducted using the e1071 package in R (Dimitriadou et al., 2008) using a radial kernel function. Leave-one-sample-plot-out cross validation carried out in the current study ensured that both feature selection and accuracy assessment were spatially independent of the validation.

The hyperspectral classification accuracy was assessed on 23 field plots. The hyperspectral imagery classification methodology differed somewhat from the methodology applied for ALS and multispectral. The methodology adopted here was the same as used in previous studies of Dalponte et al. (2008, 2009). Starting from the ground measured trees, the crowns of the trees were manually defined on the hyperspectral data, considering only trees that are visible and not covered by shadows. For tree species classification based on hyperspectral data 1122 segments were used (51% spruce segments, 38% pine segments, and 11% deciduous segments). The pixels of each crown have been extracted and two sets have been created, a training and validation set. A tree (and thus its pixels) can belong to only one of these sets. As the number of features is pretty high, in order to reduce the computational complexity and to avoid the Hughes's phenomenon (Hughes 1968) a feature selection was applied to the data of both sensors. The method adopted is based on the Sequential Forward Floating Selection algorithm (Pudil et al., 1994) as search strategy, and the Jeffries-Matusita distance as distance measure (Bruzzone et al., 1995). As classification algorithm the Support Vector machines (Vapnik 1998) have been considered. This non-parametric classifier has shown in the past to be effective in remote sensing data classification problems (Melgani & Bruzzone, 2004), and recently has been used in many study on tree species classification (Dalponte et al. 2008, 2009). SVM classification was conducted using the e1071 package in R (Dimitriadou et al., 2008) using a radial kernel function. The model selection has been performed with a 5-fold cross validation on the training set, while the validation set was used as a final validation of the classification maps. Once the classification map at pixel level has been produced, the pixels have been aggregated according to a majority rule into the ground measured segments, in order to have a result at segment level.

5.1.4 Single-tree inventory of forest stands with a high economic value (UEF)

The Kiihtelysvaara data were used to evaluate single-tree segmentation and estimation using both direct measurements and nearest neighbour imputation. The attributes considered were species, diameter, height, volume, and various branch height properties. The estimation accuracies were evaluated in classes, which describe the success of the segmentation (Peuhkurinen et al. 2011). The estimates were also aggregated to the plot-level, where the plot volume and diameter distribution were evaluated. The corresponding result was produced using a tree-list imputation method (Breidenbach et al. 2010) and the outputs of the two methods were compared (Vauhkonen et al. 2011).

The basic step of the quality related individual tree inventory system is to map stands with high economic value. The idea is to do area based wall-to-wall mapping for the whole inventory area and to find stands with high economic value, i.e. matured stands which are ready for the final cut. The decision on stand maturity can be based either on stand age or the size of the tree stock. It is also dependent on stand site class. In this case we applied the rules of the Finnish Private Forestry (Tapio 2007) and decided to use mean diameter limit 26 cm which is typical for pine dominated stands in this part of the Finland. The model for mean diameter was constructed using area based ALS height and density metrics. Finally, the ALS based model estimates for mean diameter were classified in relation to actual ones by using the stand maturity limit 26 cm.

Our tree detection algorithm used an ALS-based canopy height model (CHM). The CHM was interpolated to a resolution of 50 cm by taking the maximum ALS point height within a pixel and filling the pixels that had no ALS hits within their area with a median filtering in local windows of 3 by 3 pixels. Hole pixels, with at least seven of the eight neighbours exceeding the height value of the centre pixel by more than five meters, were replaced with the median of the values of the neighbour pixels exceeding that threshold.

In the segmentation, the CHM was first low-pass filtered using Gaussian kernels with the size of the smoothing window increasing as a stepwise function of the heights of the CHM (Pitkänen et al. 2004). The segments were created around the local maxima using watershed segmentation with a drainage direction following algorithm (Pitkänen 2005). Pixels lower than two meters were masked out from the crown segments and small segments, at most three pixels in size, were combined to one of the neighbour segments based on the smallest average gradient on the segment boundary between two segments. The method is described in more detail by Packalén et al. (2011).

The segmentation resulted in an estimated position, height and crown dimensions (diameter(s), length, volume) for each detected tree. These estimates were used in an allometric modeling chain to predict DBHs and volumes for each tree. Specifically, the DBH was first predicted using estimated tree height and crown width in regional models formulated by Kalliovirta and Tokola (2005). The stem volumes were calculated using DBH and height estimates in species-specific volume equations by Laasasenaho (1982). The accuracy of directly measuring the CBH was also assessed and compared to different measures of the CBH. The CBH was derived from the ALS data using the method presented by Holmgren and Persson (2004), which was found most accurate in an earlier comparison study (Vauhkonen 2010).

In addition to the direct measurements, the accuracy of predicting stem attributes using nearest neighbor imputation was assessed. The imputation was carried out using the MSN method implemented in yaImpute package (Crookston and Finley 2008) of the R statistical computing environment (http://www.R-project.org/). MSN with more than one nearest neighbor (k-MSN) was additionally tested, with the values of k ranging from 2 to 10. The imputations were carried out in a leave-out-one-plot fashion, i.e. the segments belonging to the same plot as the target segment were not available as nearest neighbours.

Response variables in the imputation were the species, DBH, height, and volume of the largest tree per segment. As categorical variables were not allowed with the MSN method, the species attributes was coded into dummy variables. In the case of quality attributes (crown base height, dead branch height), which were measured from pine trees only, the imputation was carried out separately using response variables DBH, height, volume, and the considered quality attributes. In the tree-list imputation method, species-specific sums of volumes within each segment were used as response variables.

A large set of ALS-based independent variables was tested and effects of including different feature groups were also evaluated. The features were calculated either at the level of the estimation unit or at an area level, the latter being either a 250 m^2 circle in the segment approach or the full reference plot in the grid approach. The effects of including different feature groups were tested, and useless feature groups were eliminated with respect to the obtained accuracies (Vauhkonen et al. 2011). The final features included (i) maximum, mean, and standard deviation (SD) of height values (H), and proportion of H > 0.5 m; (ii) percentiles 5, 10, 20, ..., 90, 95% of the maximum H; (iii) area of the 2D convex hull of the point data calculated below 10, 20, ..., 100% of the maximum H; (iv) descriptive values of intensity distributions (I) calculated 0–40% down from the treetop; (v) area-level maximum, mean, and SD of H and proportion of H > 0.5 m; (vi) area-level proportional densities 5, 10, 20, ..., 90, 95% of the maximum H; and (vii) area-level mean and SD of I. The calculation of the features is explained in detail by Vauhkonen et al. (2010).

In the evaluation, the accuracy of both tree-level and aggregated plot-level estimates was assessed. At the plot-level, species-specific volumes and diameter distributions were considered, of which the latter were evaluated by means of error index (EI) proposed by Reynolds et al. (1988). EI was calculated as follows:

$$e = \sum_{i=1}^{k} w_i \left| f_i - \hat{f}_i \right|$$

where f_i is the true and $\hat{f}_i$ the estimated stem number of class i, k is the number of classes or bins, and w_i is the applied weight per class. The EI was calculated un-weighted, i.e. it expressed the difference in the estimated and measured distributions in terms of stem number. An alternative EI was calculated following Packalén and Maltamo (2008), who divided the absolute frequencies by the true and estimated stem number, respectively, and used a weight of 0.5 to scale the error index between 0 and 1, 0 meaning a perfect fit and 1 that the distributions do not overlap at all.

5.2 Results

5.2.1 Tree-level and area-based inventory (Central Europe Use Case – FeLis, FVA)

Table 5.2.1 shows the performance of the estimated regression models for stem volume. The seven introduced models were derived using all identified pine trees (exactly 178 trees). A model with tree height and crown diameter had the best performance with respect to the prediction accuracy determined by a leave-one-out cross-validation. The RMSE was about 24 % and the bias was 1.36 %. The derived crown volume had only low importance. This may be likely due to estimation difficulties, as further discussed by Straub and Koch (2011).

The supervised k-means algorithm produced in total seven tree parameters (tree top position and tree height, and the derived parameters from each detected ALS point were maximum crown diameter, crown base height, crown height and stem volume) for nearly 156,000 trees extracted from the 77 plots of the Karlsruhe test area. Based on the field data available for 26 plots, the RMSE calculated by 2D distance measured for each matched tree top position is given in Tables 5.2.2 and 5.2.3. The accuracy assessment shows that the trees detected were in close proximity to the reference trees with an overall average RMSE of about 1.6 m.

Table 5.2.1 Goodness-of-fit and the prediction accuracies of the regression models.

No.	R^2	Adj. R^2	RMSE, m^3	RMSE, %	Bias, m^3	Bias, %
1.	0.904	0.904	0.2726	29.57	0.0203	2.20
2.	0.502	0.499	0.4834	52.44	0.1190	12.91
3.	0.491	0.488	0.5250	56.96	0.1191	12.92
4.	0.932	0.931	0.2214	24.02	0.0125	1.36
5.	0.930	0.930	0.2299	24.95	0.0146	1.58
6.	0.512	0.507	0.4967	53.88	0.1173	12.72
7.	0.932	0.931	0.2228	24.18	0.0129	1.40

Table 5.2.2 Plot-wise RMSEs for the tree locations. The total RMSE was 1.57 m.

Plot No.	RMSE	Plot No.	RMSE	Plot No.	RMSE
p1028	2.00	p1243	1.60	p2246	1.49
p1055	1.74	p1244	1.57	p2309	0.85
p1174	2.08	p1245	1.77	p2310	1.15
p1175	1.65	p2017	1.48	p2350	1.14
p1176	1.96	p2056	0.93	p2353	1.39
p1210	1.70	p2083	2.06	p2356	2.20
p1213	1.66	p2182	1.81	p2416	2.05
p1214	1.45	p2183	1.85	p11151	1.98
p1242	1.39	p2194	0.73		

Table 5.2.3 Species-wise RMSEs for the tree locations. The total RMSE was 1.65 m.

Species ID	Species name	Species common name	RMSE
1	Picea abies	Norway spruce	0.41
2	Pinus sylvestris	Scots pine	1.49
3	*Quercus petraea*	Oak	2.12
4	Fagus sylvatica	European Beech	2.02
6	Quercus robur	English Oak	2.04
7	Quercus prinus	Chestnut Oak	1.70
8	Quercus rubra	Red Oak	2.07
9	Robinia pseudoacacia	Black Locust	1.40
10	Betula spec.	Silver Birch	1.31
11	Carpinius betulus	Hornbeam	1.86
12	Acer pseudoplatanoides	Sycamore Maple	2.35
13	*Ulmus sp.*	Elm	1.42
14	Prunus avium	Cherry	2.20

Both of the single tree detection algorithms presented above did not deliver a 100% correct result. It is always possible that for example two or more trees will not be separated and classified as one tree. On the other hand, it is obvious that a number of hits are returned from the two tree stems. Therefore a stem extraction algorithm was implemented based on the results delivered by the tree extraction algorithms in order to achieve a more correct and reliable number of trees, if possible. The stem fitting algorithm works fully automatic. Branches (horizontal ones and other ones) also detected by the test version have to be deleted manually up to now.

An example in Figure 5.2.1 shows the ability of the algorithm to fit even non-vertical stems. As input the same ALS points as described in chapter 4.1 have been used. In our opinion it is worth to include this processing step into the tree extraction and tree parameter estimation module in order to achieve better results. But the algorithm cannot be extended and included into the actual tree extraction process, as it would go beyond the scope of this project. However it is seen as a major point to consider in further work.

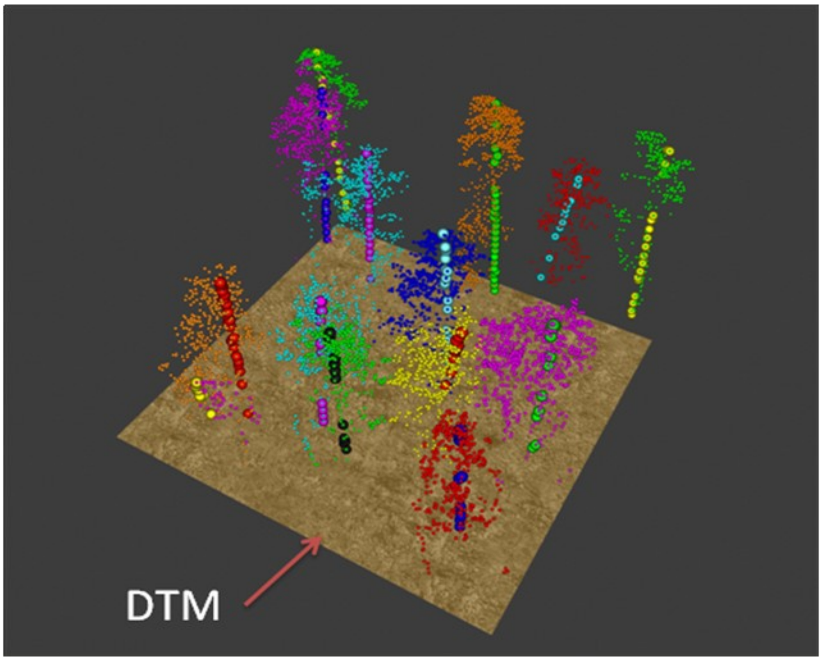


Figure 5.2.1 Single trees stems automatically fitted using a 3D ALS point cloud and the tree information extracted by one of the described FeLis tree extraction programs. The small dots are the ALS points grouped by the single tree extraction programs. The larger balls are those belonging to a fitted 3D line.

In the area-based estimation, the MSN-model showed the best performance, and thus further results are based only on it. The result of an MSN model (as all nonparametric models) is influenced by the number of neighbours used for model assessment. Therefore the influence of number of neighbours was tested for an interval between one and 20. Generally the model accuracy rises with a higher number of used neighbours. Starting from one the model accuracy rises strongly by incremental raising neighbours. The reduction of error and becomes lower and lower, with less than 0.5% by 7 to 8 neighbours, and is negotiable with higher neighbours. Therefore k=8 was chosen for model establishing (Figure 5.2.2). This is comparable to the results of Breidenbach et al. (2010).

Parameter reduction was essential for model quality. It was done by selecting the most important variables using the method varImp in the package yaImpute in R (Crookston & Finley 2008). First the best number of variables for best model accuracy was defined calculating the errors of 5% cross validation with increasing numbers of variables. The lowest errors were found with 5 and 20 parameters (Figure 5.2.3).

Because of the high variability of parameters we decided to take 20 parameters. In the second step the most important parameters were determined. The parameter selection was done separately for biomass, volume and volume proportion of coniferous wood. As the importance of variables varies in non parametric models the identification of the most important parameters was done in by calculating the 30 most important parameters in 30 runs of the model. Than the 20 most frequently used parameters were chosen. As result for Biomass estimation 7 first pulse, 11 vegetation and 2 last pulse metrics were selected. For Volume estimation 7 first pulse, 10 vegetation and 3 last pulse metrics were considered. For estimating the proportion of coniferous wood only last pulse metrics were used. Mostly cloud metrics and only a few density metrics were selected.

Volume, volume proportion of coniferous trees and biomass was predicted on 452 m^2 hexagons and stand level for the use case Karlsruhe. Errors of the models were calculated on the 374 reference plots, which were used for model establishing (Table 5.2.4).

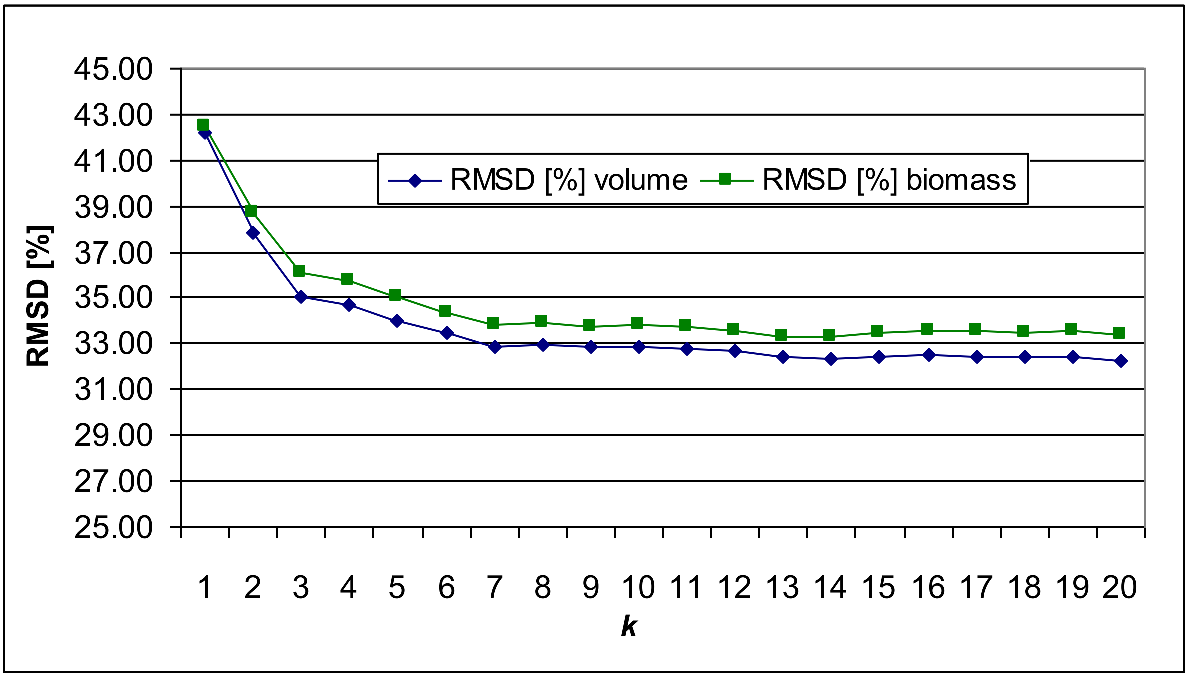


Figure 5.2.2 RMSD [%] with increasing k-value.

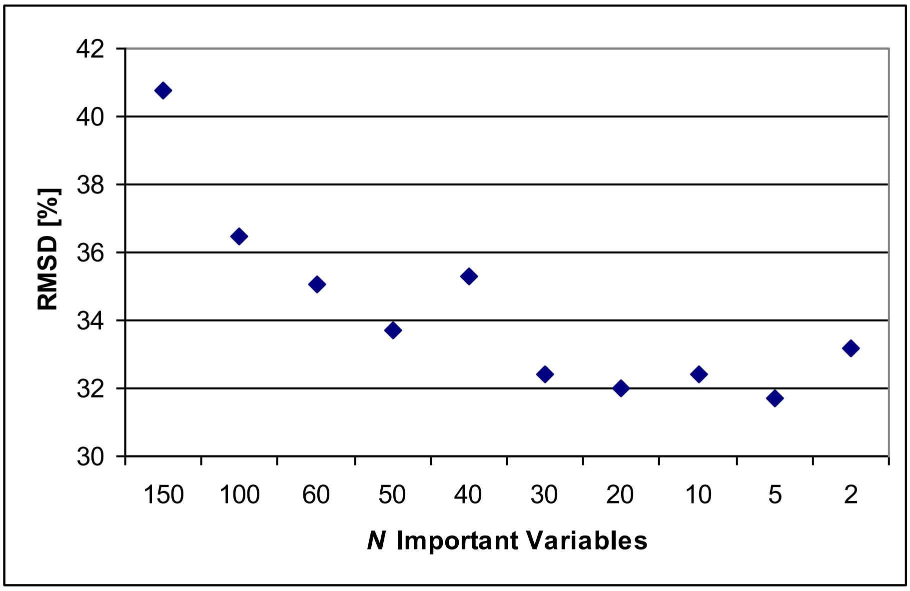


Figure 5.2.3 RMSD [%] of estimated Volume (k=8/Msn/Mean/leave5out-CV).

Table 5.2.4 RMSD of volume, biomass and proportion of coniferous wood volume estimated by MSN.

	Volume, %	Biomass, %	Proportion of coniferous wood, %
RMSD	33.04	35.16	17.55

5.2.2 Tree species classification based on synergetic use of ALS and hyper spectral image data (FORAN)

The mean values and standard deviations of the vegetation indices for each species are presented in Table 5.2.5. The three species groups (pine, spruce, and deciduous) are mostly separated in terms of the NDVI and RENDVI values as illustrated in Figure 5.2.4, although a few outliers exist. This indicates the potential for using the Vis in species classification.

Table 5.2.5 Mean and standard deviation values of the vegetation indices for the field trees.

	Mean			Standard deviation		
	Pine	Spruce	Deciduous	Pine	Spruce	Deciduous
NDVI	0.6245	0.6963	0.5802	0.033705	0.039792	0.039162
RENDVI	0.3961	0.4743	0.3231	0.038899	0.034176	0.046592

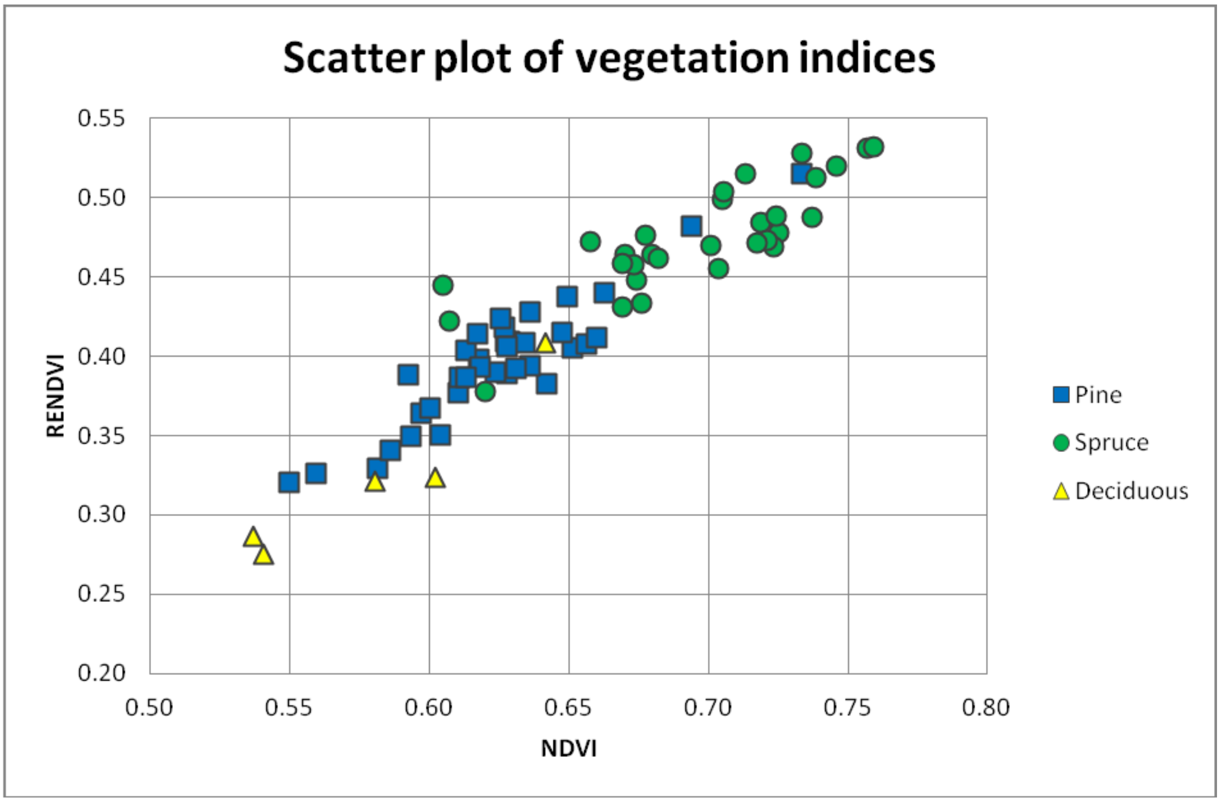


Figure 5.2.4 Scatter plot of the two vegetation indices.

An example of the detected individual tree crowns, i.e. the crown mask, and a classification result are shown in Figures 5.2.5 and 5.2.6. The classification was performed for all trees in the study area (1 048 575 trees). The division of trees in the three species groups was 35% pine, 38% spruce and 27% deciduous trees.

The evaluation was divided in two parts, one for each area. In the first area, 93% of the pine trees were correctly classified. For spruces and deciduous trees the percentages correct were 67% and 77%. In the second area only 29% of the pines were correctly classified. For spruces and deciduous trees the percentages of correct classification were 38% and 100% respectively.

A reason for the difference between the two areas is likely due to that in a sparse forest a much larger part of the tree crowns will be exposed to direct sunlight than for a dense forest. Hence, the pixels of the crown segments in the image will be much brighter. In addition, the chance that many pixels within each tree crown segment will contain a mix of spectra responses from the tree crown as well as from the vegetation on the ground is much higher. These phenomena will influence the overall response for the tree and hence also the classification result. In order to give any quantitative measure of these effects on the classification more further investigations need to be done.

In general the classification result was satisfactory. Thus, the use of VIs as basis for classification of tree species for single tress is a viable option when hyper spectral images are available. The effect of varying brightness and mix of tree crown is however a problem that needs to be studied further. A closer look at the hyperspectral images also shows large difference in brightness close to roads and at the edges of forest areas. Large shadows are also visible for trees at one side of a road, and very bright trees are on the other side. These effects should also be subject of a further investigation for.

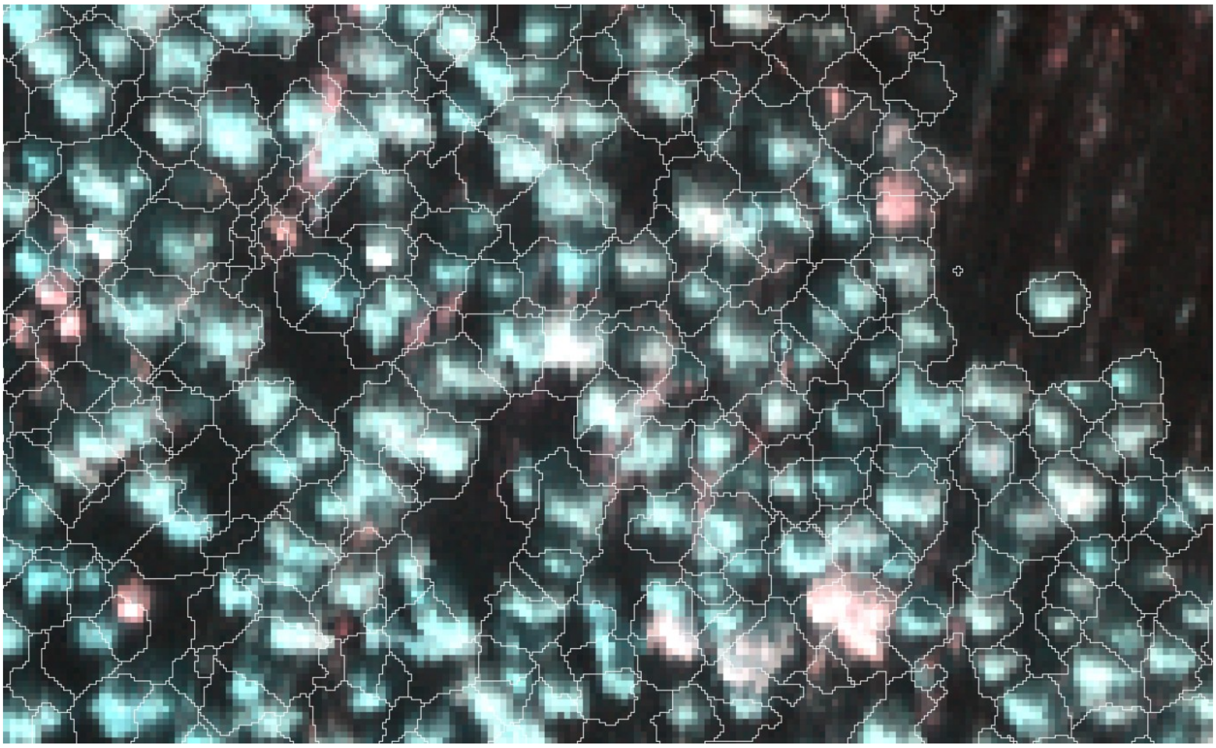


Figure 5.2.5 Single trees identified using FORAN tree detection algorithm. Pixels inside the white borders are used as classification data for the single trees.

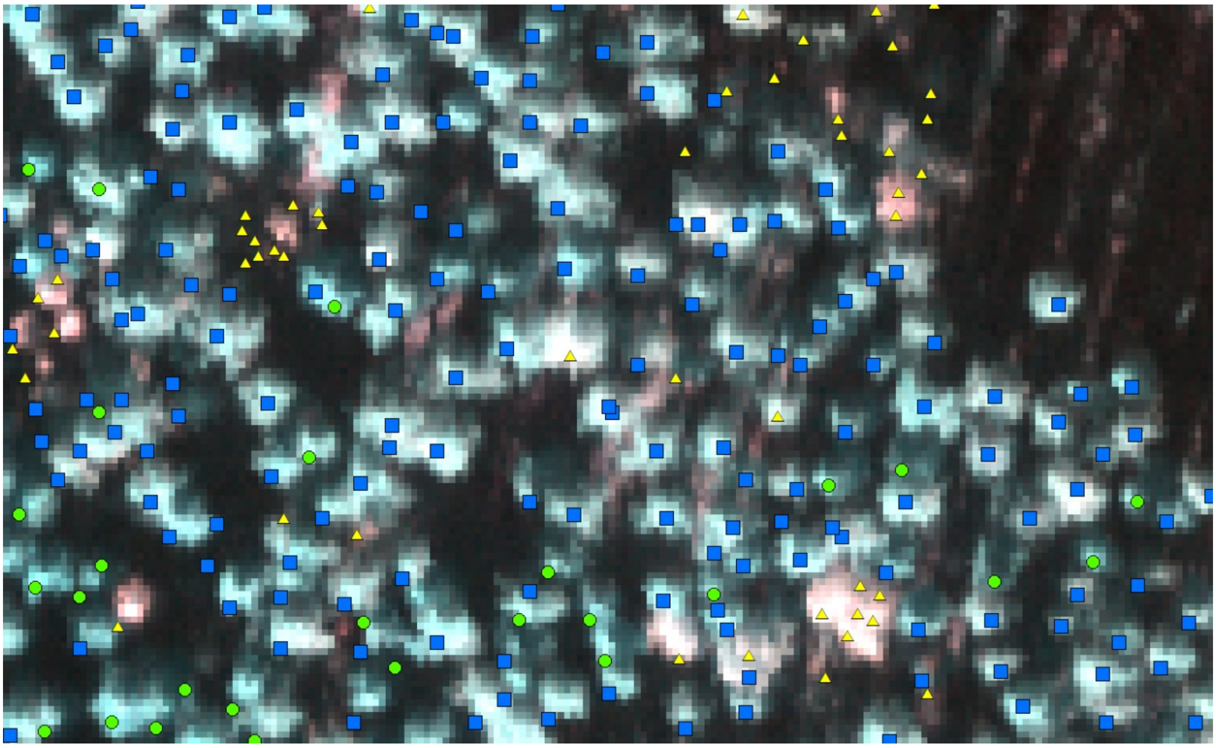


Figure 5.2.6 Classification results on the sample area. Pines are blue squares, spruces are green circles and the deciduous trees are yellow triangles.

5.2.3 Tree species recognition using ALS and spectral image data (UMB)

ALS structural information alone provided overall classification accuracies of 74–77% (Table 5.2.6). When only ALS intensity data was used, normalization of intensities increased the overall classification accuracy for tree species with 5–11 percentage points. However, adding normalized intensity information to the structural information did not improve the classification. Hence, the reported accuracies (Table 5.2.6) for ALS are only based on height- and density features. The accuracies obtained using only multispectral imagery (71–79%) were on the same level as using ALS structural information. Combining ALS structural information and multispectral imagery from the Applanix sensor and the Vexcel Ultracam D sensor provided overall accuracies of 87–89% and 84–87%, respectively. The accuracies of using the VNIR sensor provided overall accuracies of 87.8% which was nearly on the same level as the accuracies obtained with ALS and multispectral together. The hyperspectral SWIR sensor provided slightly lower accuracies (83.5%). However, both hyperspectral sensors provided accuracies which were higher than those obtained using multispectral data.

Table 5.2.6 Number of segments (N), producer accuracies (Spruce, Pine, Deciduous), overall accuracy (Overall) and kappa coefficient (Kappa) for different data sources and combinations of data sources. When different classifiers are used the range of accuracies obtained are reported.

Data source	n	Spruce	Pine	Decid.	Overall	Kappa
ALS	1520	80.2-85.8	72.3-76.2	31.3-35.7	73.9-76.5	0.57 - 0.60
Multispectral (Vexcel)	1520	62.1-76.0	80.7-84.1	46.1-67.0	70.9-75.7	0.52 - 0.57
Multispectral (Applanix)	1520	66.4-75.9	81.7-86.5	61.7-69.6	72.9-79.1	0.55-0.64
ALS + Multispectral (Vexcel)	1520	85.3-88.9	87.1-89.9	55.7-69.6	84.3-87.0	0.72 - 0.77
ALS + Multispectral (Applanix)	1520	84.7-90.0	88.7-92.1	59.1-79.1	87.2-88.6	0.78 - 0.80
Hyperspectral (VNIR)	1122	92.5	89.4	60.7	87.9	78.9
Hyperspectral (SWIR)	1122	88.0	84.9	57.4	83.5	71.1

5.2.4 Single-tree inventory of forest stands with a high economic value (UEF)

The single-tree detection algorithm produced altogether 3228 segments for the study area. The number of trees measured in the field was 5747, i.e. the success rate of the algorithm was about 56%. Examined at the level of individual plots, this rate varied between 20–99%. The theoretical potential to detect the stem volume using single-tree methods was first evaluated by comparing the field-observed total volume and stem number of the ALS-detected trees to those of all trees (Table 5.2.7). The total stem number and volume were underestimated by 46 and 13%, respectively. Pine trees were detected slightly more frequently and spruce trees slightly less frequently compared to the total, whereas the stem number and volume of deciduous trees were underestimated by 76 and 26%.

Table 5.2.7 Performance of the individual tree detection algorithm.

	Number of stems		Volume, m^3/ha	
	Bias	Bias, %	Bias	Bias, %
All trees	575.5	45.7	26.0	13.4
Pine	229.7	32.4	15.2	11.5
Spruce	112.5	52.8	5.3	13.0
Deciduous	255.4	76.0	5.5	26.1

Altogether 71 segments were ignored in the reference data due to laser-height deviating remarkably from the field-measured height (cf. Breidenbach et al. 2010). Of the remaining segments, altogether 1824 (58%) contained exactly one tree, 420 segments (13%) had more than one tree with heights less than 50% of the tallest tree, 812 segments (26%) had more than one trees with heights close to each other, and 101 segments (3%) were empty. In the following results, these cases are denoted classes A–D, respectively.

The correlation between the ALS-based maximum height and the height of the tallest tree measured per segment was 0.99 (N=2985). The direct height measurement had an RMSE of 1.59 m (9%), being underestimated by 1.41 m (8%). A calibration model of the form h=1.179+1.014* h_ALS removed the bias and gave an RMSE of 0.74 m (4%).

The correlation between the ALS-based and field-measured CBH was 0.86 (N=2067), when the field measurement was taken to the base of the lowest living branch separated by at most two dead branches (the traditional definition). The lowest living branch was separated from the living crown by more than two dead branches in 47 cases. The use of this measurement as the ground truth gave a correlation of 0.85. The ALS-based estimate was less correlated with the field measurement to the tip of the branch (0.82 and 0.81, respectively). ALS-based CBH-estimate had a minor correlation with the dead branch height. Furthermore, the latter measurement correlated poorly with any other field measurement.

The RMSE in the direct measurement of the CBH was 1.8 m (18%), including no significant bias (Table 5.2.8). The accuracy differed in tree detection classes according to Table 5.2.8. For comparison, a linear model that used ALS-based CBH and tree height estimates had R^2=0.83 and RMSE of 1.33 (13%).

Table 5.2.8 Accuracies of direct estimation of CBH and allometric estimation of DBH and stem volume,

	CBH, m		DBH, cm		Volume, dm^3	
Class	RMSE	Bias	RMSE	Bias	RMSE	Bias
All	1.8 (18%)	-0.34 (3.4%)	2.9 (15%)	-0.01 (0.0%)	102.8 (35%)	8.4 (2.9%)
A	1.3 (13%)	-0.05 (0.6%)	2.6 (14%)	-0.6 (3.3%)	87.5 (33%)	-7.1 (-2.7%)
B	1.9 (17%)	-0.25 (2.2%)	3.1 (13%)	-0.3 (-1.2%)	124.4 (28%)	1.9 (0.4%)
C	1.7 (17%)	-0.63 (6.5%)	3.4 (18%)	1.5 (7.9%)	120.7 (44%)	47.1 (17.0%)

The estimates of tree height and crown width were used in allometric models to produce DBH, and further stem volume in species-specific equations. The RMSEs were 2.9 cm (15%) for the DBH and 102.8 dm^3 (35%) for the stem volume (Table 5.2.8). The estimation accuracy differed according to success of tree segmentation (Table 5.2.8). Aggregated at the plot level, the allometric functions produced an RMSE of 16% and a bias of 9% for the total volume. It should be noted, however, that median crown width produced by the segmentation was used in the DBH model, although the model is formulated using a field-measured maximum crown width. The use of maximum segment width resulted in a serious overestimate.

The MSN imputation produced a species recognition accuracy of 88–91% depending on the number of neighbours used (Table 5.2.9). The estimates of the DBH and volume were slightly less accurate than those produced by the allometric models (Table 5.2.9), especially when using k=1. The RMSEs usually decreased as a function of the value of k. The increase in the performance was typically higher when increasing k from 1 to a few than e.g. from 5 to

10. Using imputation, the CBH estimates were improved compared to direct estimation, but the estimates of the dead branch height were particularly inaccurate (Table 5.2.10).

Independent on the measurement / modelling technique, the estimates were most accurate when the segmentation had succeeded producing one segment per tree (Tables 5.2.8–10). This result indicates that less accurate results may be obtained in forests, where trees are more interlaced.

Table 5.2.9 Accuracies of species, DBH and volume imputation, The values are produced using one/ten nearest neighbours.

	Species	DBH, cm		Volume, dm^3	
Class	Classification accuracy	RMSE	Bias	RMSE	Bias
All	88/91%	3.9/3.0 (20/15%)	0.0/-0.0 (0.0/-0.1%)	148/122 (51/42%)	-4/-9 (-1.3/-3.0%)
A	91/93%	3.5/2.6 (21/14%)	-0.3/-0.2 (-1.4/-1.2%)	123/97 (46/36%)	-11/-11 (-4.0/-4.3%)
B	88/91%	4.5/3.4 (19/15%)	-0.6/-0.8 (-2.4/-4.3%)	201/174 (46/40%)	-25/-44 (-5.8/-10.0%)
C	82/85%	4.5/3.4 (24/18%)	0.9/0.9 (4.8/4.6%)	166/141 (60/51%)	23/16 (8.3/5.7%)

Table 5.2.10 Accuracies of CBH and dead branch height imputation. The values are produced using one/ten nearest neighbours.

	Crown base height, m		Dead branch height, m	
Class	RMSE	Bias	RMSE	Bias
All	1.8/1.5 (18/15%)	0.0/0.1 (0.4/1.0%)	3.7/2.8 (112/85%)	0.1/0.1 (1.7/3.7%)
A	1.5/1.2 (16/13%)	-0.1/0.0 (-0.9/-0.3%)	3.7/2.7 (107/79%)	-0.1/0.0 (-2.2/0.1%)
B	2.4/2.1 (21/18%)	1.0/0.2 (0.8/0.2%)	3.6/2.8 (124/97%)	-0.2/-0.1 (-5.9/-2.2%)
C	1.9/1.5 (20/16%)	0.3/0.4 (3.4/3.7%)	3.5/2.8 (121/96%)	0.5/0.5 (18.0/17.8%)

When aggregated at the plot-level, the single-tree imputation technique produced an RMSE of about 17% and a bias of about 19% for the total volume (Table 5.2.11). The species specific volumes were estimated less accurately. The tree-list imputation method (Breidenbach et al. 2010) gave unbiased estimates, but the RMSEs were close to those produced by the single-tree imputation. Two plots with deviating forest attributes (Figure 5.2.7) considerably affected the accuracy figures. These plots consisted of very large trees, being pines on another plot and spruces on another, and the reference data did not include similar observations for imputation. Without these plots, the RMSEs of the total, pine, and spruce volume were 28.7, 27.0, 17.4 m^3/ha, respectively, using the single-tree imputation (k=1), and 25.7, 36.7, and 16.1 m^3/ha, respectively, using the tree-list imputation (k=1). The RMSE for the deciduous volume remained at the same level with both the methods.

Table 5.2.11 Accuracy of estimating volume (m^3/ha) at the plot-level.

	Single-tree imputation		Tree-list imputation	
	k=1	k=10	k=1	k=10
Total volume, RMSE	34.2 (17.3%)	38.3 (19.4%)	34.7 (17.5%)	32.5 (16.5%)
Total volume, bias	22.6 (11.4%)	24.9 (12.6%)	1.6 (0.8%)	2.1 (1.1%)
Pine, RMSE	52.3 (38.5.3%)	49.0 (36.0%)	50.9 (37.4%)	48.1 (35.3%)
Pine, bias	16.5 (12.2%)	13.4 (9.9%)	5.9 (4.4%)	5.1 (3.7%)
Spruce, RMSE	42.2 (104.5%)	33.7 (83.3%)	27.2 (67.4%)	27.0 (66.7%)
Spruce, bias	0.4 (1.0%)	3.8 (9.3%)	-3.0 (-7.4%)	-2.7 (-6.7%)
Deciduous, RMSE	19.9 (93.6%)	19.9 (93.4%)	22.8 (107.5%)	20.9 (98.2%)
Deciduous, bias	5.7 (26.7%)	7.7 (36.5%)	-1.3 (-6.2%)	-0.2 (-1.1%)

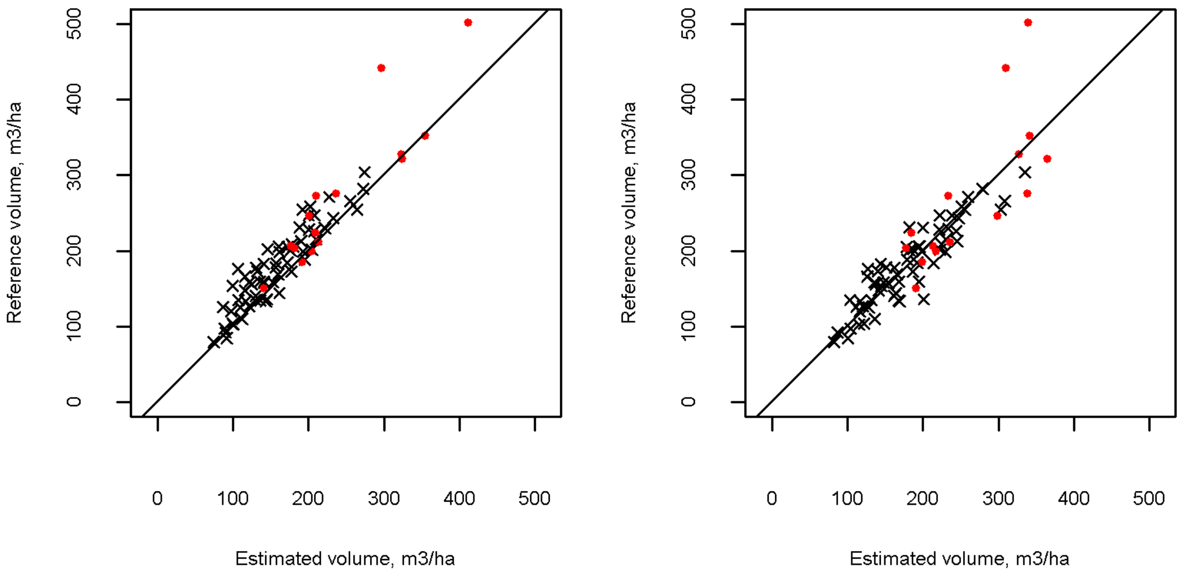


Figure 5.2.7 Estimated vs. reference plot-level volume predicted by single-tree (left) and tree-list (right) imputation methods using k=1. The estimated stands with a high economic value are shown with red dots.

The Reynolds' error index for the predicted diameter distributions was on average 831.5 using single-tree imputation and 834.1 using tree-list imputation (Table 5.2.12). The relative error index values show a similar behaviour than earlier in the volume prediction, i.e. a better fit with respect to the total distribution using the tree-list imputation, but more equal values between the two methods in species-specific predictions. The relative values are notably lower than those reported by Packalén and Maltamo (2008).

Table 5.2.12 Reynolds' error indices for the predicted diameter distributions. The values in the parentheses are calculated using relative stem frequency.

	Single-tree imputation		Tree-list imputation	
	mean	SD	mean	SD
All trees	831.5 (0.40)	428.4 (0.13)	834.1 (0.33)	338.5 (0.10)
Pine	418.5 (0.23)	282.6 (0.11)	485.7 (0.21)	247.2 (0.10)
Spruce	174.2 (0.09)	304.4 (0.14)	230.4 (0.10)	314.5 (0.13)
Deciduous	322.9 (0.12)	377.6 (0.12)	355.8 (0.13)	308.8 (0.08)

The detection of the stands with a high economic value had a success rate of 95%. The estimated stands are highlighted in Figure 5.2.7. The area-based model for the mean diameter had an RMSE of 1.6 cm (7.7%). Two stands were incorrectly classified in both classes. In these stands, the predicted diameters were close to the limit (about 25 cm and 27–29 cm). The accuracy of estimating volume for these stands was low due to including the two high-volume stands. However, the area-level approach shows a way to allocate field measurements to these stands.

Furthermore, ALS intensity showed different values between plots dominated by different species (mainly pine vs. other species), indicating an ability to detect stands with single species. This difference was related to proportions of different types of pulses. Pine-dominated plots produced multiple returns per pulse more frequently than other species. As a consequence, the plots with pine proportion >95% were separated from others with 90% accuracy. At individual tree level this difference was not as clear. Segments of pine and spruce were separated with 95% accuracy using a single ALS-intensity-feature, independent on tree size. Deciduous trees were mixed with both coniferous species in both intensity and structure features.

6. Mapping and modelling of wood resources and quality integrating terrestrial sensor techniques

6.1 Methods (IWW)

In the following the process steps are described to gain information about geometrical parameters of the stem as well as information about the bark quality of trees by use of terrestrial laser scan data. By measuring scars of the bark, information about the inside quality of the stem can be deduced. The latter is gathered as part of Task 6100 where stems are scanned internally by use of a CT device. Also there, the corresponding data are processed. This work is done from the project partner FVA.

The trees within the Flexwood project which were scanned from different positions and which bark was analyzed to deduce information about the interior quality of the stem are from the German test site in Karlsruhe. Here, 15 Beech trees were selected and 14 of them scanned (Trees A to O with Tree J missing as it was felled by the forest administration before scanned by a terrestrial laser scanner). All selected trees had a BHD between 25 and 50 cm and possessed multiple scars and buckles.

Prior to scanning, the remaining trees were surveyed to relate them to the official German Gauß-Krüger coordinate system. They were also marked to relate the terrestrial laser scan data and the data gathered by the CT device to each other (see Figure 6.1.1). On different sides of the trees crosses with a different number of bars were attached to the stem. As the tree was then cut every 4.2 m being the maximal length for scanning in the CT device, the crosses were attached at the height of 1.3 m, 5.2 m, and 9.4 m. All 14 trees were scanned from four different positions, each scanner position around 4 m close to the tree. They were then felled and cut in 4.20 m long parts. All scars were measured interactively and then scanned in the CT device as part of work in Task 6100.

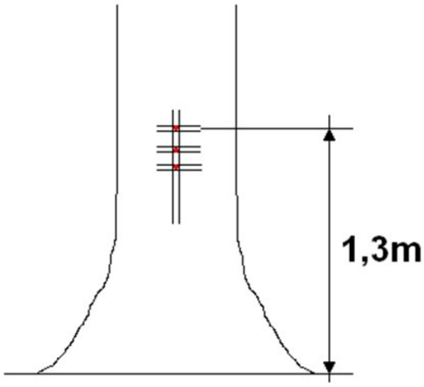


Figure 6.1.1 Marking of the trees to transform different coordinate systems to each other.

As a preliminary step for the determination of quality parameters of trees by use of terrestrial laser scan data the estimation of stem diameter in different heights by use of single scans was evaluated. The intensity image of a single scan of the tree stem, i.e. from one side without the effort to orient different scans of one environment to each other, needs to be processed. The stem is isolated and aligned so that the diameter can be assessed by calculating the three-dimensional distance between the left and the right edge of the stem.

Each tree was then separated from the point cloud so that only the stem remained. The stem was then approximated by consecutive cylinders. The starting point of this algorithm is a point on the surface of the stem. At this height, the shape of the stem is approximated by a circle. In the distance, defined by the user as the height of the cylinder, a second circle is calculated representing the average diameter of the tree at this height. These steps are repeated continuously after shifting the cylinder by the defined cylinder height up to the length of the stem. Afterwards the same procedure is applied to the stem starting again from the starting point but in downwards direction. When the algorithm reaches the lower end of the stem, the stem is represented by multiple cylinders. The middle point of each cylinder, the direction of the cylinder axis and the cylinder height are stored in a specific file. An example is shown in Figure 6.1.2.

The cylinder approximation can be used to calculate taper, volume, and sweep for each stem. The volume is calculated by amounting the volume of all cylinders. To calculate sweep out of the cylinder file, the directions of the cylinder axes are taken into account. Starting from the first point, the vector to a point which is more than 2 m distant is built. The heights from all vectors between two adjacent points to this vector are calculated. The maximum value serves as starting value for the next cycle.

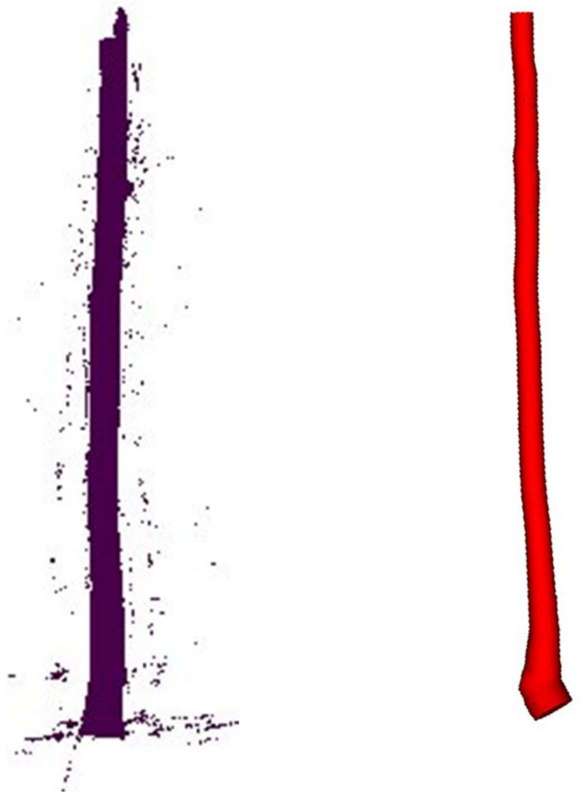


Figure 6.1.2 Point cloud and cylinder approximation of a tree stem.

The intensity value of the laser beam mapped on each scan point delivers a rather realistic view of the bark of each tree. The range value offers some further information. By use of this additional information, bark characteristics can be identified. To support this analysis by image processing methods the three dimensional shape of each stem is mapped onto a plane. This is done by a sequence of coordinate transformations (Figure 6.1.3).

The point cloud of the tree stem is transformed from a Cartesian three-dimensional coordinate system into a cylindrical coordinate system. The initial system is the scan coordinate system (denoted as X,Y,Z_{Scan}) where one of the scanner positions is the origin and all other scans are oriented towards this system. Altogether, they represent the whole point cloud of the lower part of the tree. To transform this coordinate system into one where only the complete visual part of the stem is represented (denoted as X,Y,Z_{Stem}), an affine transformation of the middle points (upper and lower end) of the stem as middle points of a cylinder are used. The line between these two middle points is also the axis of the cylinder. With these two points a translation and a rotation is calculated. All points of the stem are then calculated as cylindrical coordinates (denoted as Cylinder) with the cylinder above as reference. By use of the diameter and height of the cylinder and the resolution the three dimensional points of the stem are mapped into plane image coordinates (denoted as Row, Col_{Image}). As there are some points in overlapping areas where parts of the stem are assessed by two different positions of the scanner the program decides which scan should be used to represent a specific part of the stem. This is affected by the angle from the scanner position to the stem point.

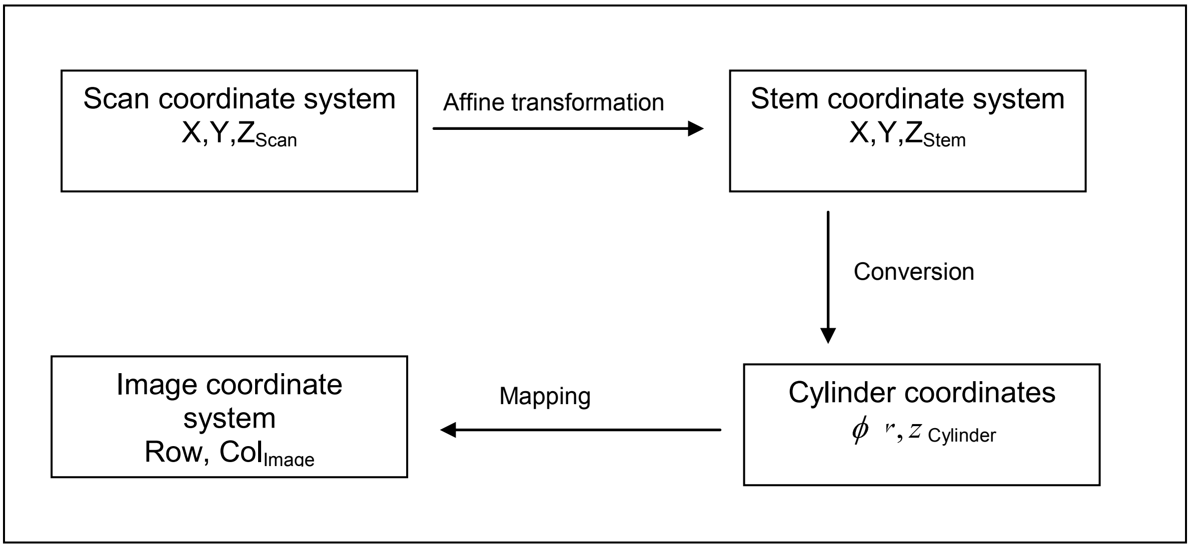


Figure 6.1.3 Coordinate transformation and conversions from scan coordinates to image coordinates.

After applying these transformations to the original data, characteristics of the bark can be identified and measured. The measurements are assisted by several supporting functions. Besides basic functionality to enhance the sight on the images auxiliary objects can be attached to the image, i.e. lines or points to highlight measurements. After determining the size of the bark characteristic they can be named and classified. The position of the bark characteristic can be denoted in image coordinates as well as in stem coordinates. Automatic handling of these images by use of image processing routines leads to an emphasis of these parts of the bark which may cover bark characteristics. The ones with scars and Chinese Moustaches are highlighted interactively.

The improvement of the method described above resulted in a three-dimensional approach. Here, a height model of each scar was developed by relating the distance of the elevation due to the conjoined branch to the flat bark. By visualizing these distances compared to a height model the profile of the scar is visible and here, the characteristic can be measured.

To connect these data to the CT data, the trees were marked prior to scanning as described above. The middle points of these crosses were then measured in the TLS data and also in the CT data. The coordinates of these identical points in both coordinate systems were used to calculate the transformation parameters: three translations, three rotations and scale factors (number dependent on the quality of the coordinate measurements). To identify the exterior position of the characteristics in the CT data all of them needed to be marked prior to the CT scans. While doing this as part of work in Task 6100, FVA also measured all of the scars manually. The results gained there are used to compare them with the measurements gained by use of TLS data.

6.2 Results (IWW)

All information deduced from the intensity images is dependent on the resolution of the point cloud which is dependent on the distance of the scanner to the measurement area. The point density of the data gathered on the Karlsruhe test site is 6.3 mm in a distance of 10 m to the laser scanner. When scanning from different sides of the tree the data is overlapped and here, a denser point cloud can be acquired.

To get the position of the trees the registration of the scans per tree is required to determine the middle of the tree stem. In our approach this point is determined as the middle point of the lowest cylinder which represents the approximate shape of the stem. The accuracy of the coordinates depends upon the accuracy of the cylinder fitting which can be evaluated by comparing it to diameter measurements by use of a calliper. Height of the lowest green branch and height at crown base can be determined by use of the intensity image. For the sample trees all branches up to the height of 9.4 m were cut as these trees needed to be marked up to this height. Diameter measurements can be achieved by identifying the edges of the stem in the intensity image when the tree is scanned only once from one position. It could be shown that after taking into account distance, vertical angle and the expected distance, the mean deviation from diameter estimation out of TLS data to calliper measurements is 0.38 mm (± 0.04 mm SD).

As all 14 trees were scanned from four different sides, the diameter was determined by approximating the stem by consecutive cylinders. The DBH was measured manually prior to felling, so that these values can be compared to the diameter results gained by analysing the cylinder output for each tree. The difference between the two measurements is visualized in Figure 6.2.1. The RMSE calculated from these values is 0.50 cm (1.3 %) and bias –0.34 cm (0.9 %).

The difference between the measurement taken by both techniques lies between -1.19 cm and 0.25 cm. The maximum difference with more than one centimetre deviation can be regarded as an outlier and may be due to bad scanning data caused by obscuring vegetation. Even with this outlier the standard deviation is ± 0.36 cm. The main distinctive feature is that the differences are mainly negative which is caused by the filtering of TLS data prior to processing where points especially at object edges tend to lie at the wrong position.

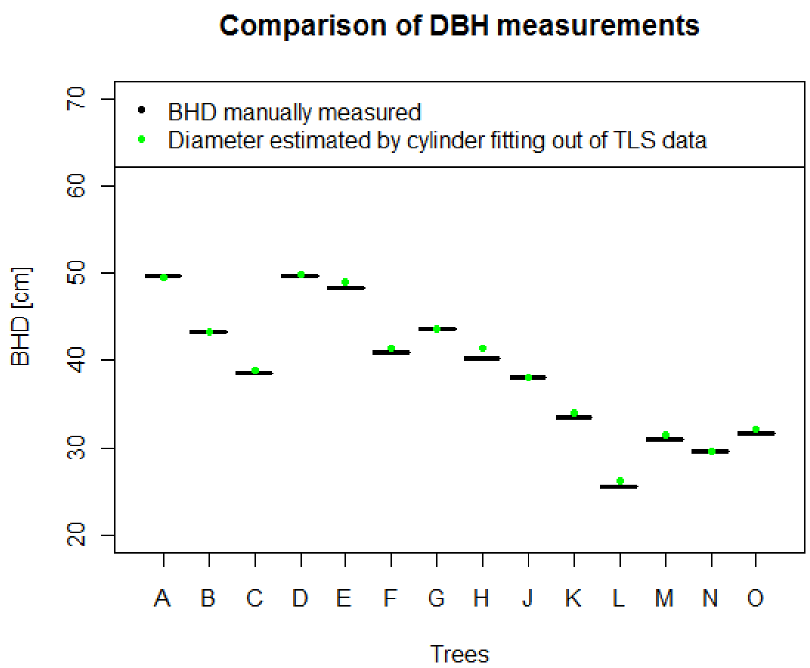


Figure 6.2.1 Differences between the manually measured (reference) DBHs and the DBHs resulted from the cylinder approximation calculated by use of the TLS data for each tree. The black bars indicate the reference DBH and the green dots represent the diameter values gained by use of TLS data.

The bark characteristics were measured manually as part of work of Task 6100 and then determined out of the TLS data. The same stem characteristic can be identified in the mapped intensity image of the TLS data (Figure 6.2.2). The mapped intensity images are then processed by a program to highlight the parts with bark characteristics and then measured. It can be shown that most of the values are higher when estimated by use of TLS data in comparison to the manually measured barks. To enhance the data used for measuring the bark characteristics height models were developed where the flat bark represents the ground surface (Figure 6.2.3).

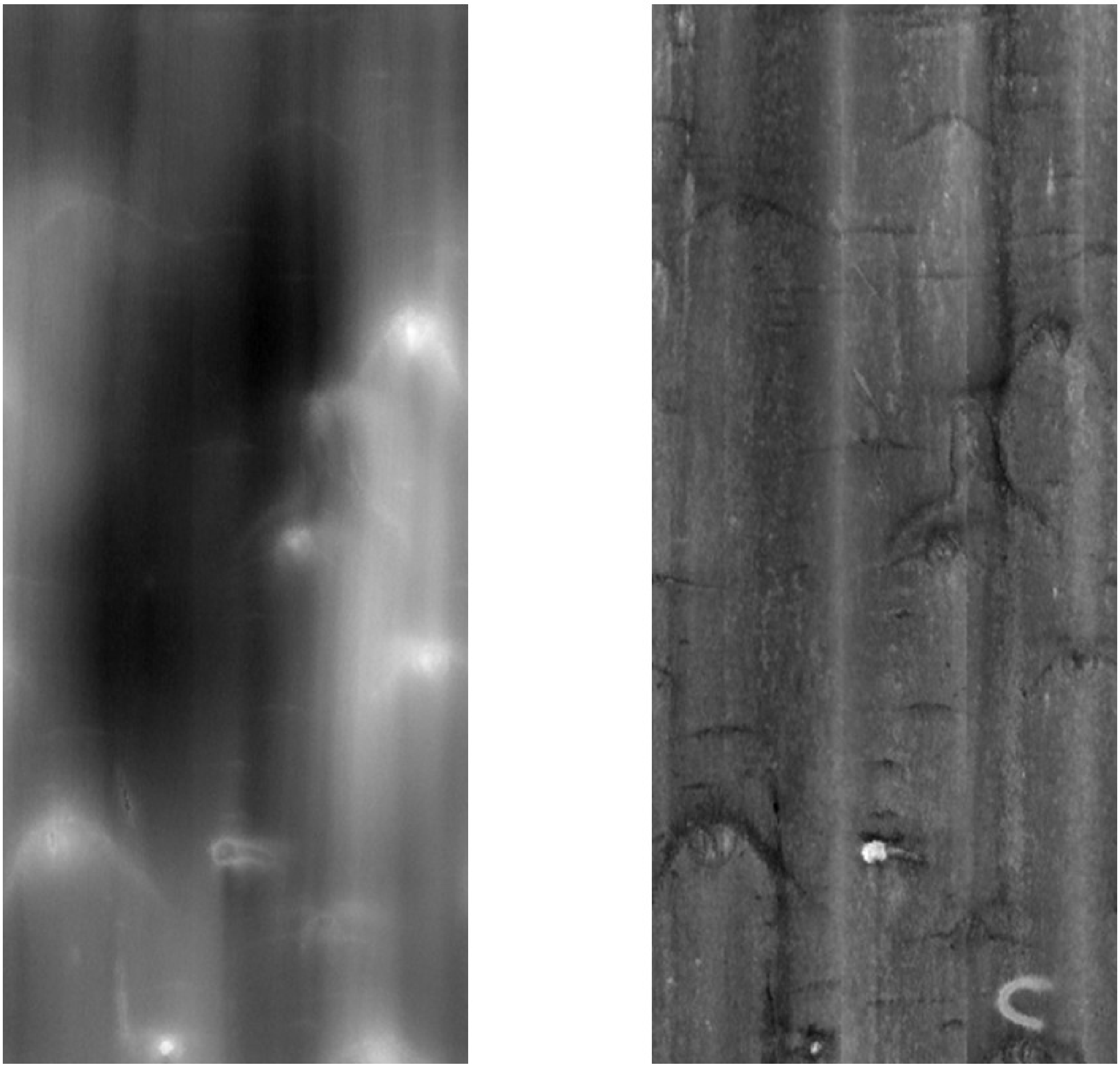


Figure 6.2.2 Range (left) and intensity image (right) of a stem part after mapping the image data onto a plane.

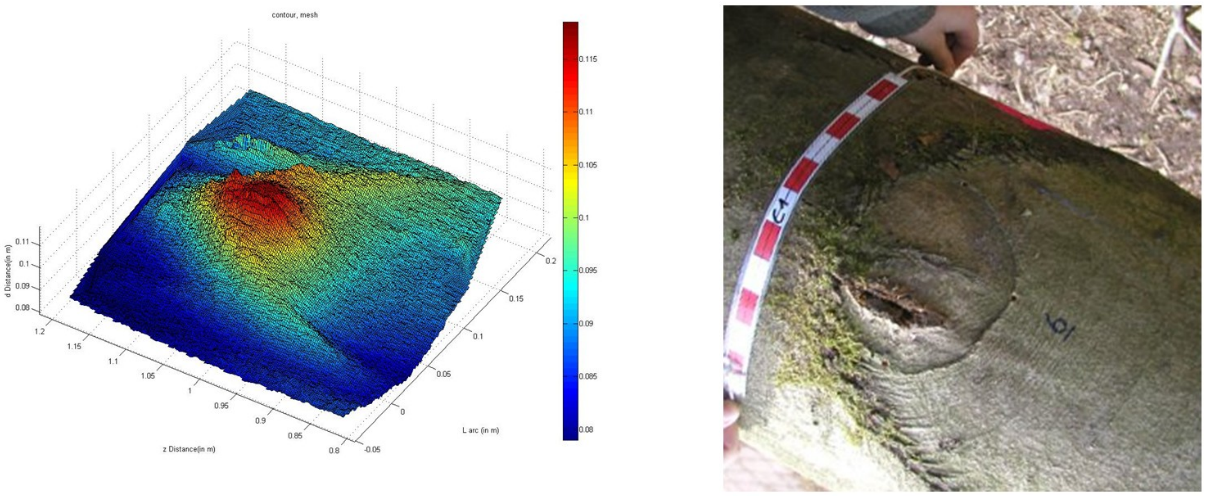


Figure 6.2.3 Height model (left) of a bark characteristic shown in the right side of the figure. The shape of the bark characteristic is visible and can be measured from the height model.

7. Integrated concepts for description of tree and wood properties in the forest

7.1 Methods

7.1.1 Integration of tree data from ALS and TLS (FVA, FeLis, UEF)

In this work we compared manually measured tree parameters and stem parameters obtained from TLS point cloud analysis done by TreeMetrics. Methodology for linking stem positions from two separate datasets was developed. Also, a species classification method based on using TLS point clouds as a reference for ALS data was developed and tested.

All scans took place in the area of the use case “Karlsruhe” on 40 terrestrial inventory plots. In 22 of these plots all tree positions were terrestrially measured. All plots were exactly geographically referenced and permanently marked. The north definition was in all cases done with a handheld compass. The scans were registered together with TreeMetrics on 4 days in December 2010. We had about –10°C and snow fall most days. The scanner had been positioned exactly above the centre point of the inventory plot.

First, the proportion of trees detected by the Treemetrics software and the accuracy of the stem positions was evaluated. Stem extraction was limited to a radius of 15m around the scan position and only trees within this circle were compared. We analysed the frequency of detected trees and their distance to the scanner. The hypothesis was that bigger stems are more likely to be detected than smaller stems. Therefore the mean dbh of stems within increasing distance-classes to the scan centre was analysed.

Second, methodology for linking ALS and TLS datasets was developed. Within Flexwood, various datasets from different sensor types are incorporated and analysed. In the sections 5–6 before single trees were extracted out of ALS and colour infrared data as well as point clouds gathered from terrestrial laser scanners. However both datasets weren’t used as one distillate combining the information from both datasets. To generate a higher level of information in new sensor supported inventory we developed a hierarchic combination approach to attach the information coming from TLS (sweep, diameter each 10cm) with the parameters extracted from ALS (height, crown base height and maximum crown diameter). Therefore we consider three features:

1. The distance between ALS- and TLS-trees
2. The maximum crown diameter of the ALS-trees
3. The dbh of both tree sets, whereas the dbh of the ALS-trees was estimated by a general, species independent height function.

If a TLS-tree doesn’t meet the criteria mentioned above it doesn´t get matched. An initial list of candidates is produced by three different approaches. The first one is only considering the 2D-distance between ALS- and TLS-trees. The other two are taking the information of the third dimension coming from TLS-trees into account. Here the leaning of the tree, which is reflected in the changes of the stem centre positions along the extracted trees is taken into account. We either approximate the potential tree top with a 3D line fitting algorithm or we span a 3D-box around the estimated tree from base to top. We calculate intersections and 3D-distances to find possible matching candidates. For a detailed description of the methodology see Fritz et al. (2011).

Third, in addition to matching tree positions extracted from both ALS and TLS data, we compared the canopy point clouds of these two data sources in terms of 3D texture. Particularly, we examined species-specific properties of the shape distributions obtained combining shape modelling and sampling techniques (Edelsbrunner & Mücke 1994, Osada et al. 2002), with an aim to use the TLS-based shape distributions and related field observations as a direct training/reference dataset for species estimation based on ALS shape distributions. To ensure data quality in both ALS and TLS, a restricted test dataset was composed, consisting of the dominant trees detectable by single-tree algorithms (Vauhkonen et al., in press) within up to 10 m from the TLS location. As a result, altogether 114 trees (58 pines, 23 beeches, and 33 oaks) of different sizes were considered. The ALS and TLS point data were extracted from a circle with a radius corresponding to the tree size and a position corresponding to the location of the ALS height maxima. The radius was determined as the crown width calculated using the field-measured DBH and height in species-specific models by Pretzsch et al. (2002). In the TLS data, the height-above-ground values were calculated using the minimum height of at least 10 TLS points with the same height value as the ground level. TLS points higher than the corresponding ALS height maxima were filtered out.

The envelope of both ALS and TLS point surfaces was modelled using the alpha shape technique. An alpha shape (Edelsbrunner and Mücke 1994) is based on the Delaunay triangulation of a point cloud such that each simplex of the triangulation is compared with the specified alpha value in the computation phase. Those simplices, which have an empty circumsphere with a squared radius larger than the defined alpha value, are removed. Thus, an alpha shape can be regarded as an alpha-weighted Delaunay triangulation. The resulting shape depends on the parameter alpha: with small values, the shape reverts to the input point set and is the convex hull of it with very large values. Here, two alpha values were tested: a fixed value of 1.5 m based on experiments with the data, and a quasi-optimal alpha value selected separately for each point cloud so that the resulting alpha shape included the point data within a single connected component. The alpha shapes were generated using the point data above 40, 50, 60, 70, 80 and 90% of the maximum height. The determination of the shape distribution was based on sampling two random points from the alpha shape surfaces and calculating a Euclidean distance between the points (Osada et al. 2002). The distances obtained as a result of 10,000 iterations were arranged to a distribution of values between 0 and 1 such that the maximum distance corresponded to value 1. The species estimate for each ALS shape distribution was obtained as the species of the most similar TLS distribution in terms of Minkowski distance of order one, the computation of which basically corresponds to an un-weighted Reynolds’ error index (see section 5.1.4). The accuracy of the species estimation was evaluated using leave-out-one-plot cross-validation.

7.1.2 Calibrating ALS based quality related tree attribute estimates at stand level by using field measurements (UEF)

Tree detection and segmentation was based on the methods presented in the chapter 5.14. As a result large set of tree and plot level ALS variables were obtained (see also 5.1.4), These variables were used to model tree attributes, namely DBH, Tree height, Volume Crown Base Height and Dead Branch Height. Only Sots pines were considered and the data were divided to modelling and validation data including 56 plots and 14 plots, respectively, The exact number of trees in modeling varied according to modelled tree attribute and was 433 in validation data. Mixed-effects linear models (Lappi 1991) were used in the modelling. These models take into account the hierarchical structure of the data and allows the calibration of the models by using field measurements.

In a system of mixed-effects models, the stand effects and residuals may be correlated. This correlation can be utilized to predict the stand effects of all models if the response of even one of the individual models from one or more sample trees of the plot has been measured (Lappi 1991, Lappi et al 2006, Siipilehto 2006). In this study, the model system included the models for DBH, Tree height, Volume, Dead branch height and Crown Base Height. The models were estimated separately, and cross-model variance-covariance matrices of residuals and stand effects were estimated using the realized stand effects and residuals of the modeling data (Lappi et al. 2006). The measured tree specific variables in tree different (A-C) strategies were: A: DBH, Tree height, Dead Branch Height and Crown Base Height; B: DBH, C: DBH, Dead Branch Height and Crown Base Height. The measurements were taken from 1 - 10 randomly selected trees of the validation plot. The accuracy of the prediction was evaluated using the remaining trees of the plot.

7.1.3 Integrated concept for description of tree and wood properties in the forest – Northern Europe use case (Skogforsk)

This section gives a general description of individual trees including, geographical position, diameter, height, tree age, tree species and external properties (e.g. stem defects) to be used as an input to WP 5000.

7.2 Results

7.2.1 Integration of tree data from ALS and TLS (FVA, FeLis, UEF)

Within the 22 full inventory plots 1037 trees were terrestrially measured. Altogether 868 trees were detected automatically from TLS by analysis of TreeMetrics. This gives an overall detection rate of 84%. The probability of tree detection decreased with increasing distance to the scan centre. In some cases more trees than existing trees have been detected (Figure 7.2.1). The mean dbh of detected trees was in nearly all scan distances lower than the mean dbh of terrestrial measured reference trees (Figure 7.2.2). However there is no clear trend of increasing dbh of detected trees with increasing scan distance.

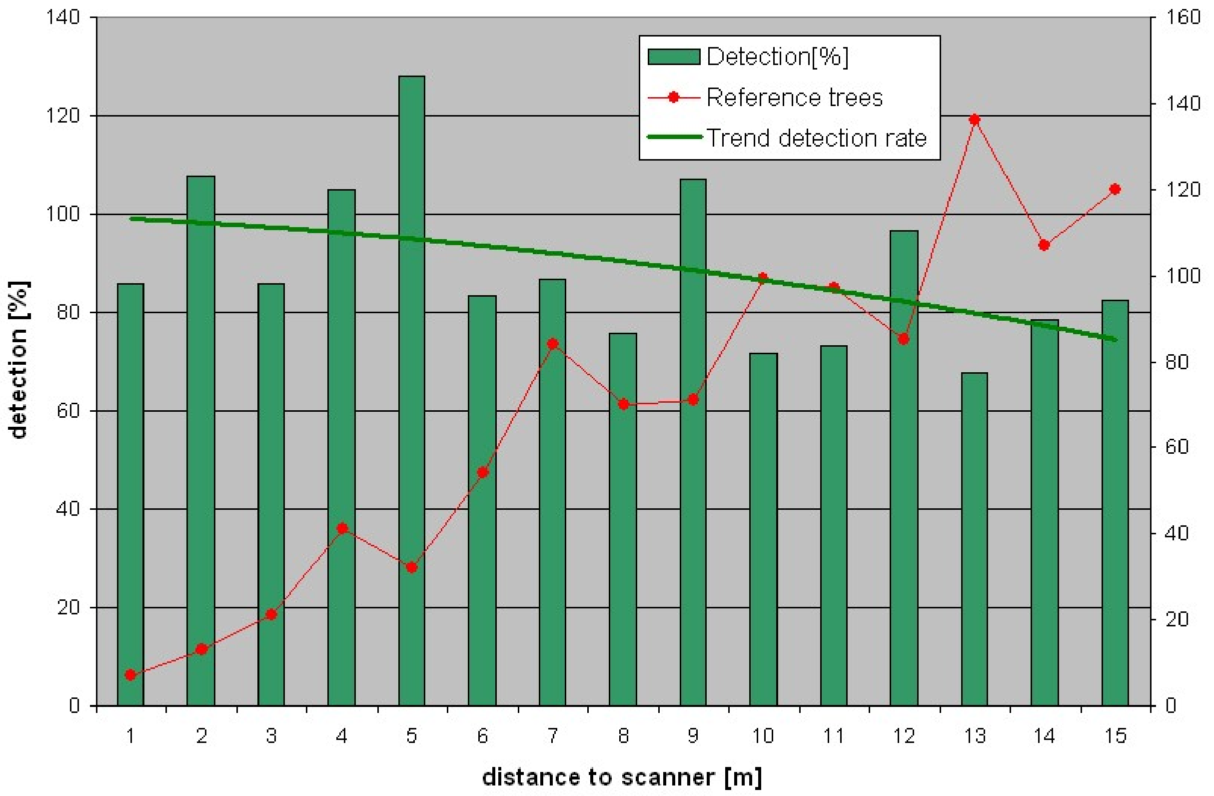


Figure 7.2.1 Tree detection rate according to scanner distance.

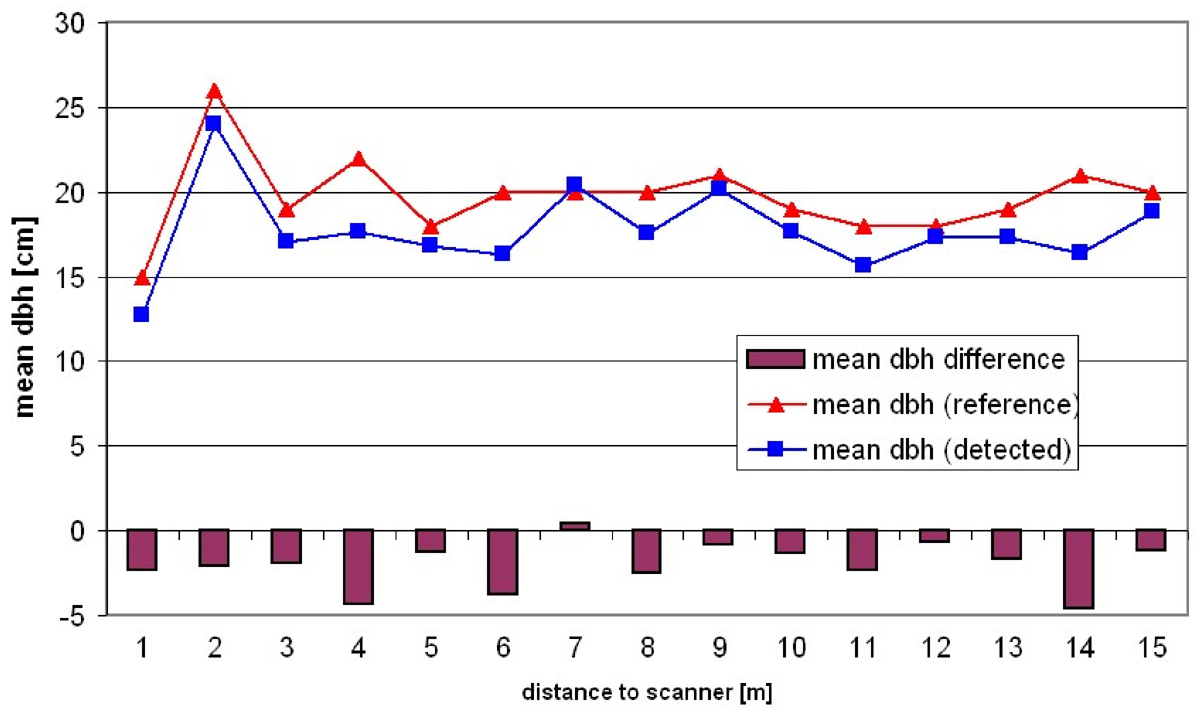


Figure 7.2.2 Mean dbh of the detected trees according to distance to the scan centre.

Figure 7.2.3 shows an example of reference trees and automatically detected stem positions within one sample plot. This is an ideal situation, were no error in direction registration of the scan occurred. Unfortunately many scans had a problem with the north definition. It was very time consuming to find and repair these errors by turning the stem positions around the scan centre with logic angles e.g. noted north deviation, or 90 or 180 degrees. A problem which can be avoided easily by carefully noting north direction, deviation and scan direction during scanning and consequently applying it during data processing.

Distance from a TLS detected stem to the nearest reference trees was calculated in order to give an idea about the accuracy of tree location. About 70% of the detected trees have a reference tree within less than 50 cm, 90% of them have a reference tree within one meter (Figure 7.2.4). Analysing the difference between measured and automatically detected dbh both under and over estimation exists. However more dbhs are underestimated than overestimated (Figure 7.2.5). Looking at the absolute dbh difference between reference and TLS detected trees. It shows a good overall accuracy (Figure 7.2.6). About 40% of the trees had less than 1 cm difference in dbh, about 60% less than 1 cm, and about 80% less than 4 cm difference in dbh.

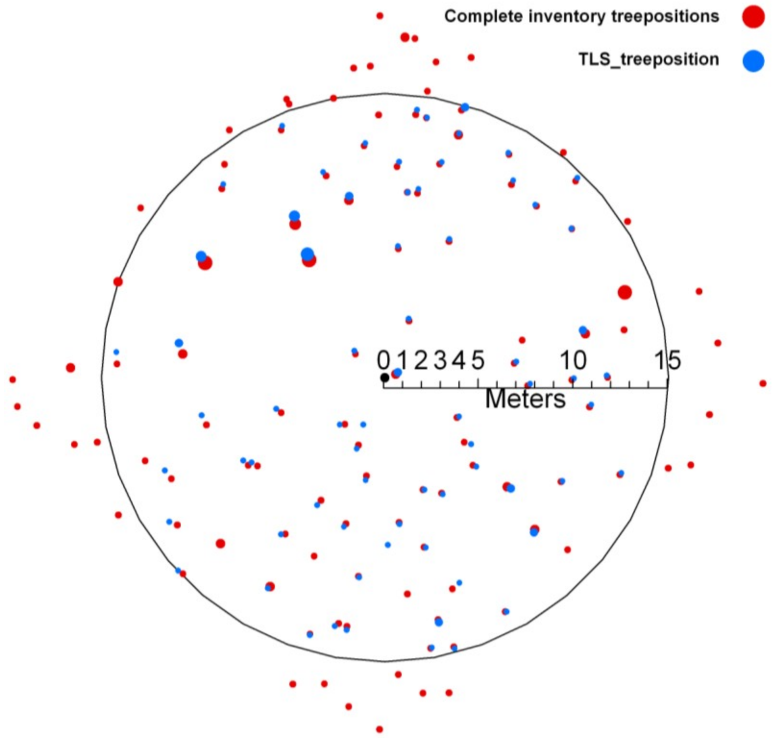


Figure 7.2.3 The positions of the reference and the TLS-detected stems (point size according to the dbh).

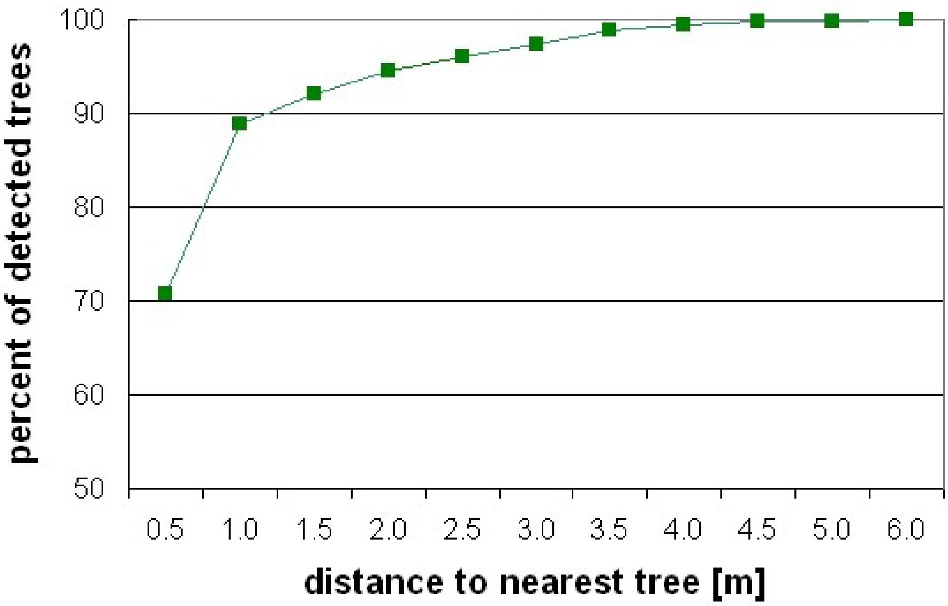


Figure 7.2.4 Distance to nearest reference tree.

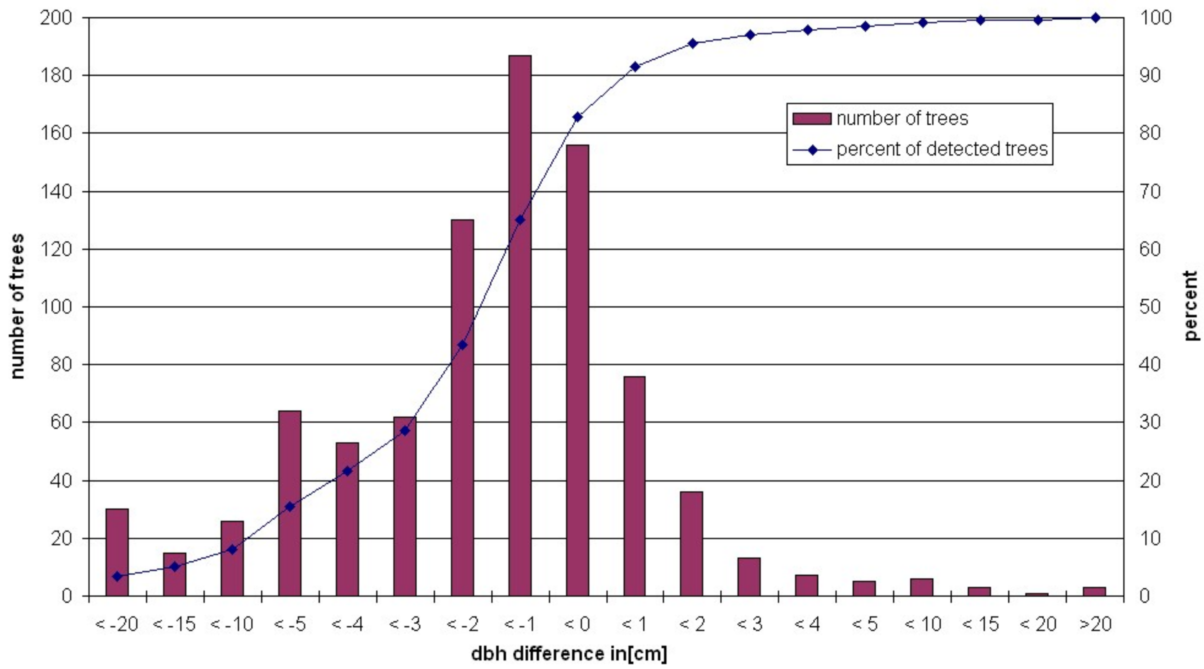
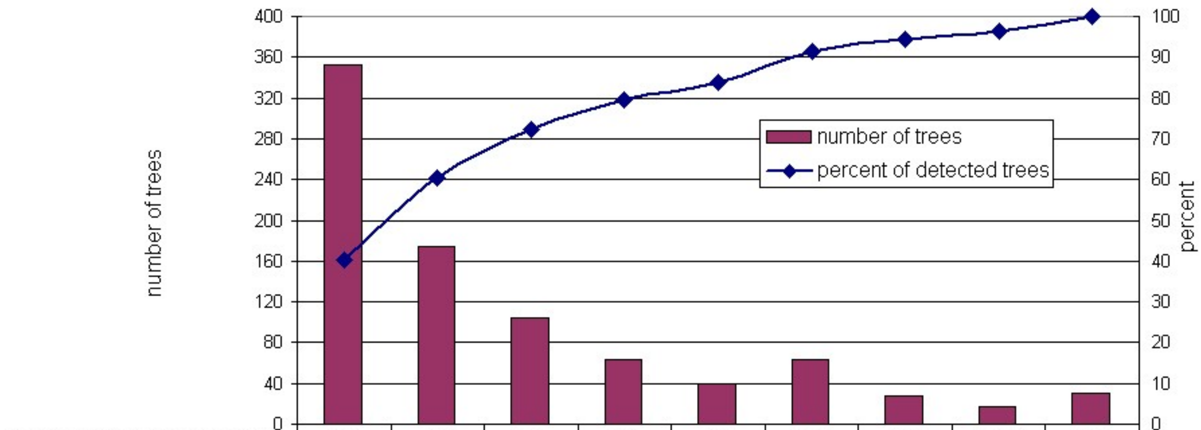


Figure 7.2.5 Dbh difference (TLS-detected – reference dbh).



absolute dbh difference [cm]	< 1	< 2	< 3	< 4	< 5	< 10	< 15	< 20	> 20
number of trees	352	174	104	63	40	64	28	17	31
percent of detected trees	40	60	72	79	84	91	95	96	100

Figure 7.2.6 Absolute difference between the TLS-detected and the reference dbh.

Using the method developed for linking the ALS and TLS detected trees, nearly half of the TLS-trees could be associated to an ALS-tree, depending on the initial list creation method. The 2D-distance and 3D-line fit list creation performed best. The matching rates for these methods were 41 and 48%, respectively. With 3D-boxes, the matching rate was 24%.

The analysis of the shape distributions extracted from ALS and TLS data indicated a potential to separate beech from the other two species considered. The distributions were most distinct using data from above 40–60% of the maximum height and an alpha value fixed to 1.5 m. The two data sources produced distributions of rather similar shape, although not perfectly matching to each other (Figure 7.2.7).

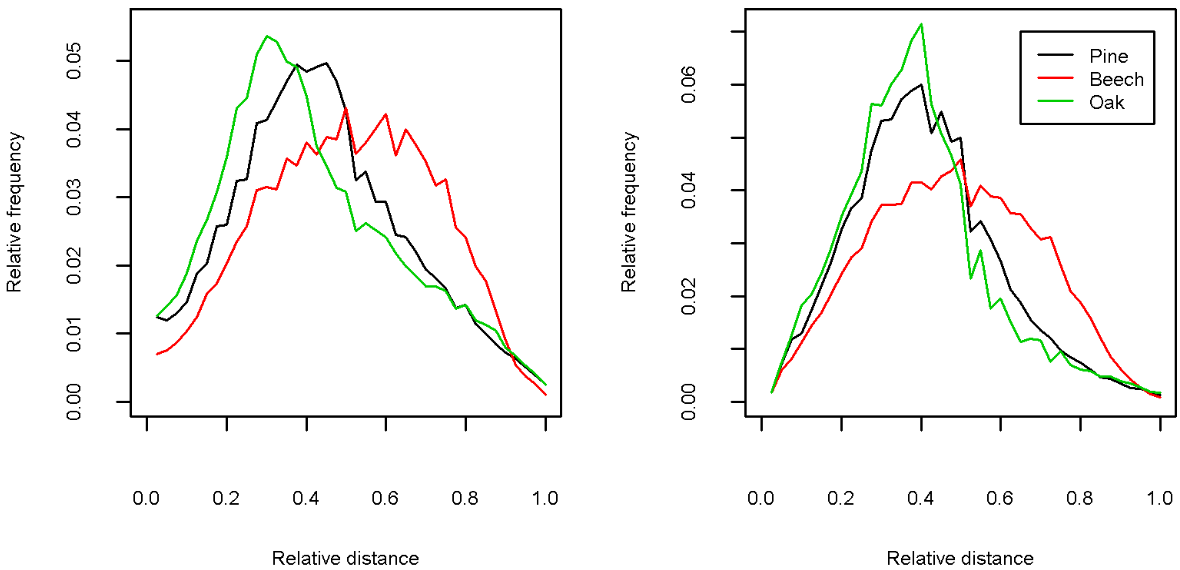


Figure 7.2.7 Average shape distributions obtained from TLS (left) and ALS data above 50% relative height (alpha value 1.5 m).

The highest classification accuracy was obtained by comparing the distributions calculated from all relative heights (40–90%) simultaneously (alpha 1.5 m). The classification produced a confusion matrix shown in Table 7.2.1 and an overall accuracy of 60.5% (kappa 0.31), while the performance was slightly lower using the quasi-optimal alpha. The classification accuracies using individual height layers varied from 42% (κ 0.13) to 57% (κ 0.27) with the fixed alpha value, and from 43% (κ 0.09) to 53.5% (κ 0.20) with the quasi-optimal alpha value.

Table 7.2.1 Classification result using shape distributions calculated from relative height levels 40–90% with an alpha value of 1.5 m. Overall classification accuracy 60.5% (kappa 0.31).

		Observed species		
		Pine	Beech	Oak
Predicted species	Pine	47	5	26
	Beech	3	15	0
	Oak	8	3	7

Despite the low overall accuracy, the method showed a potential to discriminate between pine and beech (88.6% accuracy) and beech and oak (88% accuracy) (Table 7.2.1), when a further improvement could be obtained by a prior classification to coniferous and deciduous trees using aerial images (e.g. Heinzel et al. 2011). The classification accuracies could also possibly be improved by TLS data collections designed for the current purpose (trees scanned from multiple directions). If successful, using the proposed method the field reference data collection for species classification could possibly be replaced by TLS data libraries including the scanned trees with a species observation. Here the extraction of the point data was based on field data, however, and a further verification using an automated segmentation method is required.

7.2.2 Calibrating ALS based quality related tree attribute estimates at stand level by using field measurement (UEF)

The constructed models for tree attributes consisted always fixed effects part (Table 7.2.2) and random effects part (Table 7.2.3) including random Plot variable and one ALS variable are the following. It is notable that ALS based tree height is used in all modles except in the case of Crown Base Height.

The main idea of constructing the tree attribute models was to show the performance of different calibration strategies. Basically, already measurement of one tree attribute of one tree in plot calibrates all tree attribute models but we tried to mimic what would be the suitable calibration strategies in different field measurement applications. The results are shown in Figure 7.2.8.

The results show that all strategies improve the accuracy of DBH prediction. In the case of Tree Height, the attribute in consideration must be included to calibration variables to obtain any improvements in accuracy. This is the case for both RMSE and bias. This may be due to the close correlation between ALS based tree height and field measured tree height. In the case of tree volume all the measurements improve accuracy but if only DBH is measured the effect is minor. It is worth to notice that also the measurements of branch attributes improve the accuracy, so it is not necessary to measure tree height at all to improve volume predictions. The results are more contradictory in the case of Crown Base Height. The measurement of DBH only has no effect and the measurement of branch attributes first worsen the accuracy and it is improved only after measurement of five sample trees. For

Dead Branch Height the calibration effects are more clear; the measurements of branch height characteristics improve accuracy- Also the absolute improvement is largest from the RMSE of 2.1 meters to RMSE 1.5 meters. The results are correspondent for the derived tree attribute: length of the dead branch section which has been found to be important external tree quality characteristics (e.g. Maltamo et al. 2009b).

The results of this experiment showed that in most case the accuracy of ALS based tree attribute prediction is improved with field measurements if mixed-effects models and BLUP calibration is applied. The practical importance of these results lies in pre-harvest measurement applications where marked stands are field visited. It is also worth to notice that these calibration measurements may be based on TLS scanning.

Table 7.2.2. Fixed parts of the constructed tree attribute models. In the models a denotes that the variable has been calculated from the 250 m2 area around tree, elsewhere tree level variables are used, h20,…h80 are height percentiles, hmax is maximum height value, hmean is mean height value and veg is proportion of vegetation hits above 2 meters.

Variable	DBH	Tree Height.	ln(Volume)	Crown Base Height	sqrt (Dead Branch Height)
Intercept	7.435	1.243	-3.849	0.354	-0.719
hmax	2.439	0.781	0.216		0.045
h20				0.630	
sqrt(h30)	-4.902				
ln(h70)			1.020		
h80		0.257			
a_hmean	-0.828			0.247	
ln(a_veg)				1.469	
a_h30			-1.551		
a_h70					0.072

Table 7.2.3. Standard deviations of random effects of the constructed tree attribute models. Correlation between Plot and ALS variable is presented in brackets.

Variable	DBH	Tree Height.	ln(Volume)	Crown Base Height	sqrt (Dead Branch Height)
Plot	2.461	0.702	0.409	0.930	0.638
hmax	0.192 (-0.902)	0.052 (-0.913)	0.027 (-0.922)		0.046 (-0.811)
h20				0.096 (-0.772)	
Residual	2.738	0.689	0.319	1.064	0.347

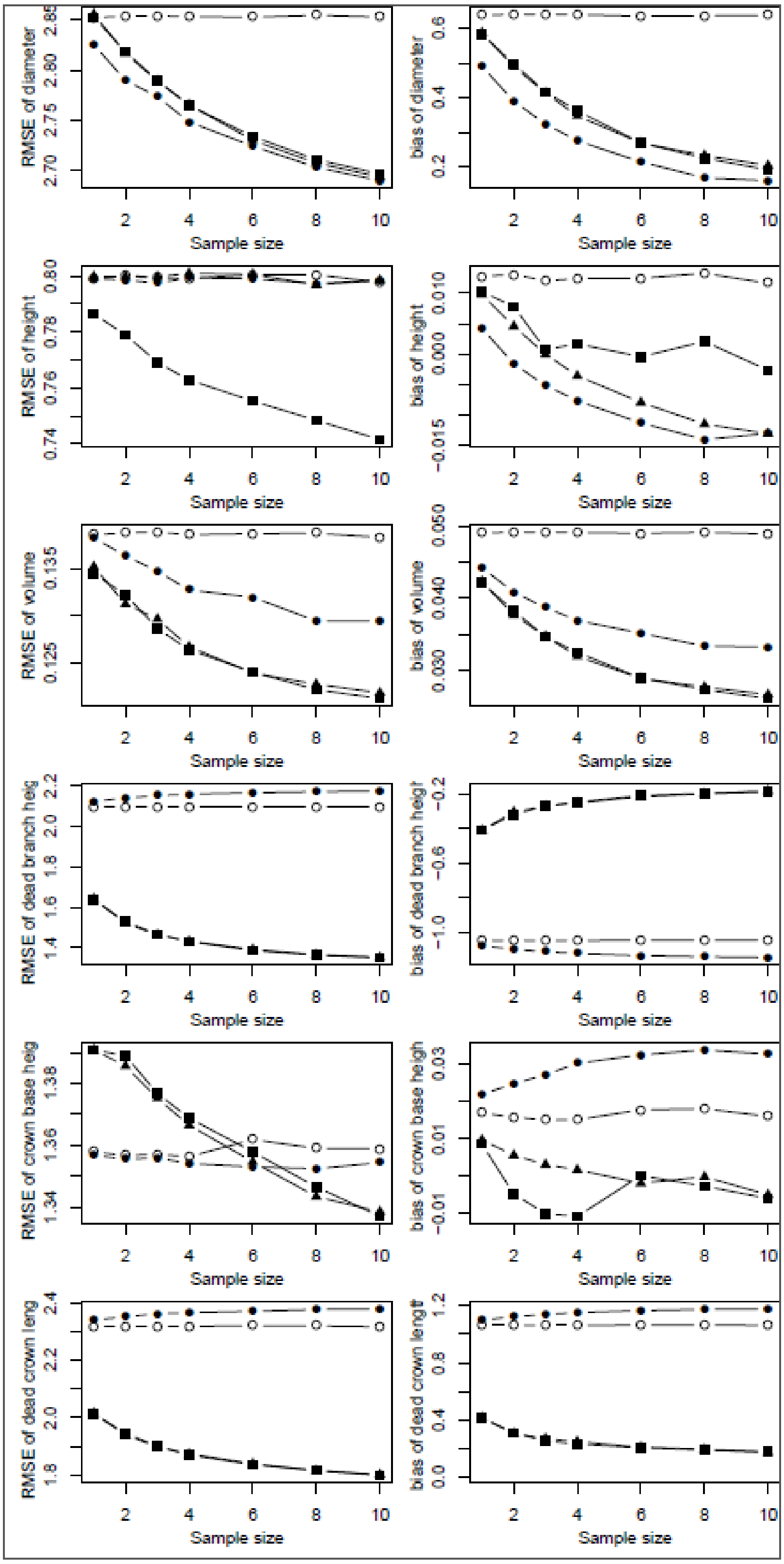


Figure 7.2.8. The results of the different calibration strategies by means of RMSE and bias of tree attributes. Additionally results concerning the length of the dead branch section in a stem are presented. The number of calibration trees varies between 1 to 10. The different calibration strategies are square = measurement of DBH, Tree height, Crown Base height and Dead Branch Height, triangle = measurement of DBH, Crown Base height and Dead Branch Height, black circle= measurement of DBH and white circle is prediction with the fixed part of the model only without any field calibrations.

7.2.3 Integrated concept for description of tree and wood properties in the forest – Northern Europe use case (Skogforsk)

An overview of the preferred data sources to provide tree and forest data serving advanced logistics is given in Table 7.2.4. The results are described at stem level with the description of a single tree. Bucking simulations are based on single tree data including information on stem taper. However, forestry treatments are planned and performed at the level of stand or sub-stand. Thus, the importance of accurate forest data are at an aggregate tree level including multiple trees with accurate distribution of trees according to tree size, age, species, and external properties.

Table 7.2.4 Overview of the preferred data sources to provide forest data as input to FlexWood components. X indicates the preferred sources of data used in the Northern European Use Case where (X) indicating alternative approaches.

	Remote sensing		**Field measurements**			**Other models**
	ALS	Optical sensor	TLS	Stand inventory	Harvester	
Geographic position	X		(X)			
Diameter (DBH)	X		X			
Stem taper			X			(X)
Height	X					
Tree age				X		
Tree species	(X)	X		(X)	(X)	
External properties			X		X	(X)

<u>Geographic position</u>

The geographic position of a tree gives information on how many trees that are found within a harvest area. The main advantage is the independency from previous made stand delineations. The borders of a stand can change during the planning process, for example some parts of a stand are normally excluded from harvest due to environmental considerations (e.g. FSC Sweden, 2010). Sometimes only parts of a stand are treated. Changes in stand borders will have an impact in the number of trees that will be harvested and therefor also the forecasts of product recovery. Position of individual trees within a forest stand can be of interest in stands with large variations of tree size or tree species composition. For large stands harvest operation are going on during a longer period and the production might change over time due to spatial variations in tree size or tree species composition. As an input to bucking simulation and the following planning average geographic position and average tree ages of the stand are used as additional input for predicting wood properties (e.g. Moberg, 2000; Wilhelmsson et al. 2002). Geographic coordinates are also used for timber logistics.

The requirements in the FlexWood system are to provide a map of trees that can be used to estimate the number of stems accurately. The map of trees can also be used to describe the spatial distribution of different products within stands. The resolution from ALS provides sufficient and reliable information on trees geographic positions. Based on ALS data most of the dominating trees are detected (i.e. Persson et al. 2002) and also the locations of the undetected trees can be theoretically predicted based on tree list imputation (cf. Packalén et al. 2011). If ALS data are missing, TLS can provide information on the number of stems and spatial variation at the stand level. In such cases, estimates of the number of stems can be improved by counting stems on sample-plots.

Tree size

The tree size provides data essential to estimate the number of logs and size of each log. The basis for tree size includes height and diameters for a tree stem. Multiple diameter measures along the stem also define the stem taper which is required to estimate log diameters (i.e. Arlinger et al. 2002).

Estimates on tree heights are based on the ALS data. ALS gives accurate height estimates for all detected trees within the area of interest. Based on height and crown diameter measurements by ALS and/or imputation techniques, DBH are also estimated for the detected trees. For the planning process of timber flow accurate height and diameter distributions at the stand level, not necessarily keeping track of each individual tree may be sufficient (cf. Barth et al. 2008). DBH and stem taper can be estimated based on TLS measuring the stem diameter on the visible sections of the stem for a sample of trees. To estimate stem diameter in sections that are hidden by branches and other vegetation stem taper functions are required. In stands where no TLS data have been gathered, DBH and height from ALS can be utilised as input data in stem taper functions (Edgren & Nylinder, 1949; Spångberg et al. 2001).

Tree species

Tree species is essential for many log products, saw logs as well as pulpwood. Tree species determine what products can be produced and to what customer the logs are aimed. The further production in the industry is dependent on specific tree species or mixes of tree species (cf. Forsberg 2003). As an example many saw mills are concentrating their production on one or two species.

Although the results obtained here indicate an ability to perform species classification solely based on ALS data on simple targets, the classification task should likely be based on combined data from optical sensors and ALS. So far, the accuracy of tree species classification by remote data has not been proven sufficient as a reliable basis for planning of wood flow and forestry planning (Barth et al. 2008). However, tree species classification can be based on data from historical field inventories (i.e. existing stand inventories) or more recent estimates based on harvester production files from previous thinning operations. Most commonly the species composition of a stand in Nordic forestry tends to be rather stable during a rotation period.

Stem defects

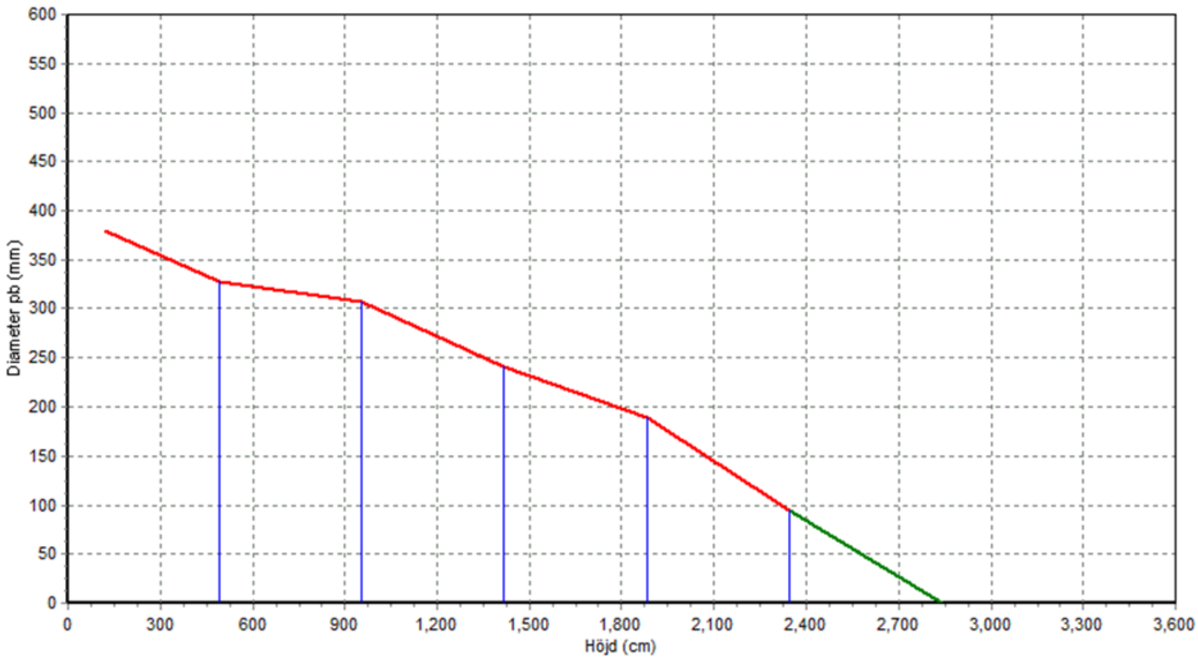
Stem defects such as butt rot, sweeps and other stem related defects are causing forced cuts at harvesting and downgrading of logs. Thus, stem defects have a large impact on the log product recovery at cut-to-length harvesting. In the examples below (Figure 7.2.8) stem defects caused a reduction of saw log volumes s between 10 and 18% of the harvested volume of timber dimensionally acceptable for saw logs.

Some stem defects, such as sweeps can be estimated by TLS-scanners (WP 4200). However, the most common stem defect and reason for downgrading of spruce logs in Swedish forest is rot. Detection of rot on standing trees requires extensive field measurements (Sundblad et al. 2008; Oliva et al. 2011). However, when a tree is harvested rot is visually detectable by the operator and registered in the harvester production file

(Figure 7.2.9). Harvester production files provide information of each log and assortment (product). Saw log dimensions that have been classified as pulp are considered downgraded because of stem defects. Statistics on the frequency of stem defects based on data from four harvested areas in Österbybruk are provided in Figure 7.2.10 and Table 7.2.5. Harvester production files are able to provide empirical data of stem defects based on the downgrading and forced cuts in the harvester. A quality and damage-type model (butt rot, sweeps/straightness) can be produced for the area based statistics from harvester production files.

Tree age

To predict internal wood properties the age of the tree is an important factor. Today there are no simple methods to estimate tree age and we are still dependent on measurements in field. In the North European Use Case, stand ages were gathered from existing stand records based on field inventories. At plot level the age has been added as a stand attribute to be imputed by using ALS data (Maltamo et al. 2009a). However, the found accuracy was modest indicating low correlation between area based ALS metrics and the age.



Stock	1	2	3	4	5
Produkt	Brännved	BM Gran	Kv 1Heby	Kv 1Heby	GM
Indikator tvångskap	Other manual	Other manual			Other manual
Längd (cm)	490	464	463	464	464
Toppdiameter (mm)	328	307	241	189	94
Volym (m3fub)	0.457	0.325	0.236	0.141	0.059

Figure 7.2.9 Example of data from the harvester production files showing a spruce tree. First two logs (blue lines) have saw logs dimensions (top diameter > 15 cm) but have been classified as forest fuel and pulp wood respectively. Since the logs have saw timber dimensions the cause is considered due to stem defects.

Table 7.2.5 Statistics of the number of downgraded logs from objects 1-4.

Log diameter class	Scots Pine	Norway Spruce
150-169	38%	21%
170-189	18%	16%
190-209	14%	19%
210-229	12%	21%
230-249	11%	23%
250-269	9%	25%
270-289	9%	28%
290-309	5%	28%
310-329	5%	30%
330-350	6%	36%
>350	5%	43%

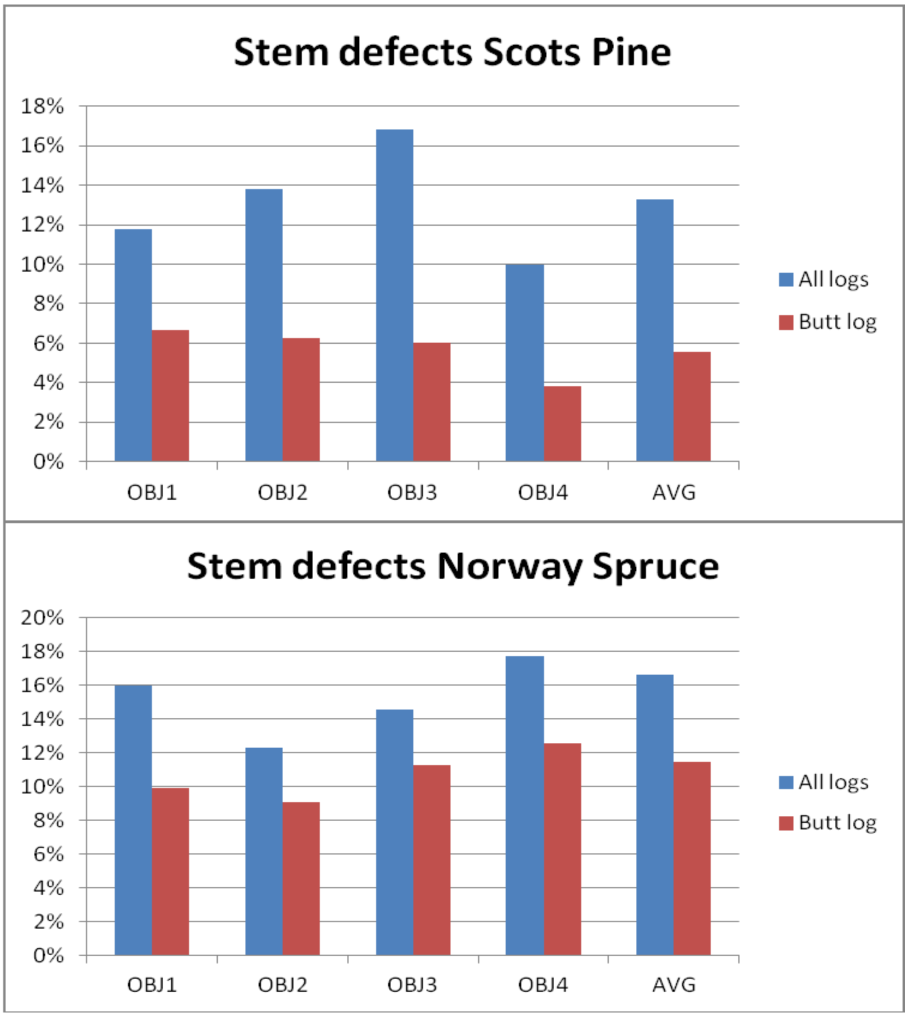


Figure 7.2.10 Example of statistics of stem defects frequencies based on harvest production files (PRI/HPR) for four different objects divided into tree species and log type.

8. Summary of the obtained accuracies

The accuracies obtained within the study are summarized in Table 8.1.1. Exclusive remarks related to the results are listed after the table.

Table 8.1.1 The best-case accuracies for the estimates of forest attributes considered within this deliverable. The errors are either classification errors in overall accuracy or RMSEs. N – number of observations.

Attribute	Test site	Data source	N	Absolute error	Relative error
Tree-level					
Species	Sweden	hyperspectral	108	-	21–62 %
	Norway	ALS	1520	-	23–26 %
	Norway	multispectral	1520	-	21–29 %
	Norway	hyperspectral	1122	-	12–16 %
	Norway	ALS + multispectral	1520	-	9–12 %
	Finland	ALS	2985	-	9–12 %
Stem volume	Germany	ALS + multispectral	178	221–525 dm^3	24–57 %
	Finland	ALS	2985	103–148 dm^3	35–51 %
DBH	Germany	TLS	14	0.50 cm	1 %
	Finland	ALS	2985	2.9–3.9 cm	15–30 %
Tree height	Finland	ALS	2985	0.7–1.6 m	4–9 %
Crown base height	Finland	ALS	2067	1.5–1.8 m	15–18 %
Dead branch height	Finland	ALS	2067	2.8–3.7 m	85–112 %
Plot-level					
Biomass	Germany	ALS	374	54 t/ha	35 %
Proportion of conifer trees	Germany	ALS	374	-	17.5 %
Total volume	Germany	ALS	374	96 m^3/ha	33 %
	Finland	ALS	79	33–38 m^3/ha	17–19 %
Diameter distribution	Finland	ALS	79	EI 832–834	-
Tree detection	Finland	ALS	79	-	44 %
	Germany	TLS	23	-	16 %
Tree position	Germany	ALS		1.6 m	-

Tree species classification accuracy was dependent on the applied estimation technique and data source. The classification could be performed based on a single data source, but in the tests carried out at the Norwegian study area, the results were improved by an integration of different data sources. In Sweden, the accuracy of the classification was tested only on two test sites, of which the site with the lower accuracy was purposively a difficult target. Despite, the variation between the sites shows the limitations in the applied methodology. In Finland, an accurate species classification result was obtained using structure and intensity features obtained solely from ALS data. However, the differences in the species composition between the study areas should be taken into account when comparing the results. In the Finnish study area, pine trees were the dominant species and formed even pure stands, whereas the species proportions were more evenly distributed in the other areas.

Stem volume prediction was tested on two separate study areas, which gave different results. The absolute error levels were higher in the German test site, where also the trees were larger, resulting in lower relative error rates. In both test sites, the estimates were found to vary highly depending on the model form or the parameterization of the nearest neighbour technique used. The best obtained results correspond with those reported earlier in Germany and Scandinavia (e.g. Persson et al. 2002, Heurich 2006, Reitberger et al. 2010, Vauhkonen et al. 2010).

ALS-based DBH and tree height estimates had a very similar accuracy compared to previous studies carried out in similar conditions (Maltamo et al. 2009b, Vauhkonen et al. 2010). Also the crown base height was estimated with a similar accuracy than earlier, and this estimate could be only slightly improved from the direct measurement (Holmgren & Persson 2004) by including field data in a MSN imputation. On the other hand, the dead branch height correlated moderately with the ALS features, and was predicted with a low accuracy.

Using TLS data, the DBH could be estimated with an accuracy of 0.5 cm (1.3 %) for the 14 trees identified clearly and scanned from multiple directions. However, the automatic procedure for detecting the trees did not find all trees (success rate of 84 %), the probability of tree detection decreasing with an increasing distance to the scan centre. In ALS, the tree detection rates tested were at the same level than in an earlier comparison of the tree detection algorithms (Vauhkonen et al., in press).

Plot-level biomass and total volume estimates had a relative error of 33–35% in the German test site and 17–19% in the Finnish test site. The difference between the estimates is likely attributed to the used estimation units, which were considerably larger in the Finnish test site, and overall differences in the forest structure. The deciduous forest are indicated to be more challenging towards the ALS-based estimation in the previous literature. In the Finnish test site, realistic diameter distributions were obtained based on ALS data and single-tree imputation, yet the distributions were truncated due to not detecting all the trees. Unbiased estimates were obtained by the tree-list imputation technique. In the Finnish test site, also species-specific plot-level volumes and diameter distributions were evaluated. The species-specific estimation was found to be less accurate compared to total attributes, yielding accuracies 35–39 %, 67–105 %, and 93–108 % for pine, spruce, and deciduous trees, respectively.

9. Conclusion

The results reported in this deliverable suggest ALS as a useful data source for estimating attributes for the trees dominating in the forest canopy, and that there are several established techniques for performing the tree-level analysis. The attributes extracted directly include the number of trees and their positions at the plot-level, and tree height and crown attributes such as width (or diameter or area), volume and length for each detected tree. The extracted attributes can be further used in estimating other tree attributes based on an allometric system of models. These direct estimates should be treated with caution, however, as not all trees were detected and the estimates were found to include systematic errors, for example.

By including local field reference data, both area-based and tree-level imputation techniques can be used to produce unbiased estimates for the attributes of interest. Besides estimation, the area-based technique was found useful for detecting stands with a high economic value, and thus allocating field measurements, for example. The predictable attributes include total volume, biomass, and proportion of conifer trees. Also species-specific plot-level volumes and diameter distributions can be predicted based solely on ALS data, at least in areas with fairly simple forest conditions and species composition. The species-specific prediction can be improved by integrating ALS with optical data from multispectral or hyperspectral images, which improve the classification result especially with respect to the proportion of deciduous trees.

TLS was found to be an effective sample-based measurement technique, enabling DBH measurements with an accuracy comparable to manually performed calliper measurements. Also, comparison to manual measurements indicates a potential to identify bark characteristics from an intensity image based on the TLS data, but these measurements and their connection to the interior wood quality will be verified in the later work (WP 6100). However, these results were based on only 14 trees scanned from multiple directions, while an automated analysis of the single-scan TLS data showed less accurate results. Not all trees could be detected and the analysis showed a tendency to underestimate the DBH. The probability of tree detection decreased with an increasing distance to the scan centre. Thus, further developments are needed to optimize the integrated use of TLS data with airborne data sources, particularly linking TLS detected trees to ALS and using this information as carried data.

In addition, this deliverable indicated and developed promising research areas and techniques that need further verification. Examples are stem detection algorithm based on high-density ALS data and using TLS shape distributions as training data for ALS analysis. Also the calibration of the airborne data-based estimates using a limited sample of field data requires further testing, and as most of the techniques rely on the use of field data, the amount of field sample plots required for reliable estimation should be generally further studied. The results obtained in WP4000 will be further used and analyzed in later Flexwood WPs.

10. References

Ahokas, E., Kaasalainen, S., Hyyppä, J., and Suomalainen, J. 2006. Calibration of the Optech ALTM 3100 laser scanner intensity data using brightness targets. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, XXXVI, Part 1/A.

Arlinger, J., Moberg, L., and Wilhelmsson, L. 2002. Predictions of wood properties using bucking simulation software for harvester. IUFRO Workshop S5.01.04 Connection between Forest Resources and Wood Quality. Harrison Hot Springs, British Colombia, Canada.

Barth, A., Hannrup, B., Möller, J.J., and Wilhelmsson, L. 2008. Validering av FORAN SingleTree® Method. Arbetsrapport 666. Skogforsk, Sweden.

Bollandsås, O.M., Maltamo, M., Gobakken, T., Lien, V. and Næsset, E. 2011. Prediction of Timber Quality Parameters of Forest Stands by Means of Small Footprint Airborne Laser Scanner Data. International Journal of Forest Engineering 22(1).

Brandtberg, T. 2007. Classifying individual tree species under leaf-off and leaf-on conditions using airborne LIDAR. ISPRS Journal of Photogrammetry and Remote Sensing 61: 325–340.

Breidenbach, J., Næsset, E., Lien, V., Gobakken, T., and Solberg, S. 2010. Prediction of species specific forest inventory attributes using a nonparametric semi-individual tree crown approach based on fused airborne laser scanning and multispectral data. Remote Sensing of Environment 114: 911–924.

Breidenbach, J., Nothdurft, A., and Kändler, G. 2010. Comparison of nearest neighbour approaches for small area estimation of tree species-specific forest inventory attributes in central Europe using airborne laser scanner data. European Journal of Forest Research 129: 833–846.

Breiman, L. 2001. Random forests. Machine Learning 45: 5–32.

Bruzzone, L., Roli, F., and Serpico, S.B. 1995. An extension to multiclass cases of the Jeffreys-Matusita distance. IEEE Transactions on Geoscience and Remote Sensing 33: 1318–1321.

Cohen, J. 1960. A coefficient of agreement for nominal scales. Educational and Psychological Measurement 20: 37–46.

Crookston, N.L. and Finley, A.O. 2008. yaImpute: An R package for kNN imputation. Journal of Statistical Software 23(10). 16 p. Available from http://www.jstatsoft.org/v23/i10.

Dalponte M., Bruzzone L., and Gianelle D. 2008. Fusion of hyperspectral and LIDAR remote sensing data for the classification of complex forest areas. IEEE Transactions on Geoscience and Remote Sensing 46 (5): 1416–1427.

Dalponte, M., Bruzzone, L., Vescovo, L., and Gianelle, D. 2009. The role of spectral resolution and classifier complexity in the analysis of hyperspectral images of forest areas. Remote Sensing of Environment 113: 2345–2355.

Dimitriadou, E., Hornik, K., Leisch, F., Meyer, D., and Weingessel, A. 2008. e1071: Misc Functions of the Department of Statistics (e1071). TU Wien, Austria.

Edelsbrunner, H. and Mücke, E.P. 1994. Three-dimensional alpha shapes. ACM Transactions on Graphics 13: 43–72.

Edgren, V. and Nylinder, P. 1949. Funktioner och tabeller för bestämning av avsmalning och formkvot under bark för tall och gran i norra respektive södra Sverige. Meddel. från Statens skogsforskningsinstitut. 38(7): 25. (In Swedish with English summary)

Eid, T., Gobakken, T., and Næsset, E. 2004. Comparing stand inventories based on photo interpretation and laser scanning by means of cost-plus-loss analyses. Scandinavian Journal of Forest Research 19(6): 512–523.

Ene, L., Næsset, E., and Gobakken, T. (in press). Single tree detection in heterogeneous boreal forests using airborne laser scanning and area based stem number estimates. International Journal of Remote Sensing.

Forsberg. 2003. Behov av informationssystem för kundorienterad virkesstyrning – Intervjuer i projekt Inforchain. Arbetsrapport 530. Skogforsk, Sweden.

Fritz, A., Weinacker, H., and Koch, B. 2011. A method for linking TLS- and ALS-derived trees. In Proceedings of SilviLaser 2011, October 16–20, 2011, Hobart, Australia, 9 p.

FSC Sweden. 2010. Swedish FSC Standard for Forest Certification including SLIMF indicators. FSC Sweden.

Gupta, S., Koch, B., and Weinacker, H. 2010. Tree species detection using full waveform lidar data in a complex forest. In Technical Commission VII Symposium – 100 Years of ISPRS, Vienna, Austria, July 5–7, 2010. Edited by W. Wagner and B. Székely, International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, IAPRS, Vol. XXXVIII, Part 7B, pp. 249–254.

Heinzel, J., Weinacker, H., and Koch, B. 2011. Prior knowledge based single tree extraction. International Journal of Remote Sensing 32(17): 4999–5020.

Heurich, M. 2006. Evaluierung und Entwicklung von Methoden zur automatisierten Erfassung von Waldstrukturen aus Daten flugzeuggetragener Fernerkundungssensoren. Ph.D. Dissertation, Technical University of Munich, Munich, Germany.

Holmgren, J. and Persson, Å. 2004. Identifying species of individual trees using airborne laser scanner. Remote Sensing of Environment 90: 415–423.

Hughes, G. F. 1968. On the mean accuracy of statistical pattern recognizers. IEEE Transactions on Information Theory, IT-14: 55–63.

Hyyppä, J., Hyyppä, H., Leckie, D., Gougeon, F., Yu, X. and Maltamo, M. 2008. Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. International Journal of Remote Sensing 29: 1339–1366.

Kalliovirta, J. and Tokola, T. 2005. Functions for estimating stem diameter and tree age using tree height, crown width and existing stand database information. Silva Fennica 39(2): 227–248.

Kändler, G. and Bösch, B. 2002. Die Betriebsinventur als Grundlage für Planung, Steuerung und Kontrolle des Forstbetriebes. Schriftenreihe Freiburger Forstliche Forschung, Bd. 18. S. 252–265.

Koch, B., Heyder, U., and Weinacker, H. 2006. Detection of individual tree crowns in airborne lidar data. Photogrammetric Engineering & Remote Sensing 72: 357–363.

Korpela, I., Ørka, H.O., Maltamo, M., Tokola, T., and Hyyppä, J. 2010. Tree species classification using airborne LiDAR - Effects of stand and tree parameters, downsizing of training set, intensity normalization, and sensor type. Silva Fennica 44: 319–339.

Laasasenaho, J. 1982. Taper curve and volume function for pine, spruce and birch. Publications of Forest Research Institute in Finland. Communicationes Instituti Forestalis Fenniae 108. 74 p.

Lappi, J. 1991. Calibration of height and volume equations with random parameters. Forest Science 37: 781-801.

Lappi, J., Mehtätalo, L. and Korhonen, K.T.. 2006. Generalizing sample tree information. In: Kangas, A. and Maltamo, M. (Eds.) Forest Inventory Methodology and Applications. Managing Forest Ecosystems vol. 10. Pp.85-106.

Liaw, A., and Wiener, M. 2002. Classification and regression by randomForest. R News 2: 18–22.

Maltamo, M., Packalén, P., Suvanto, A., Korhonen, K.T., Mehtätalo, L. and Hyvönen, P. 2009a. Combining ALS and NFI training data for forest management planning -a Case Study in Kuortane, Western Finland. European Journal of Forest Research 128: 305-317.

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

McGaughey, R. 2010. FUSION/LDV: Software for LIDAR Data Analysis and Visualization. Available from http://forsys/cfr.washington.edu/fusion.html.

McRoberts, R.E., Cohen, W.B., Næsset, E., Stehman, S.V. and Tomppo, E.O. 2010. Using remotely sensed data to construct and assess forest attribute maps and related spatial products. Scandinavian Journal of Forest Research 25(4): 340–367.

Melgani, F., and Bruzzone, L. 2004. Classification of hyperspectral remote sensing images with support vector machines. IEEE Transactions on Geoscience and Remote Sensing 42(8): 1778–1790.

Moberg, L. 2000. Models of internal knot diameter for Pinus sylvestris. Scandinavian Journal of Forest Research 15(2): 177–187.

Moberg, L. 2001. Models of internal knot properties for Picea abies. Forest Ecology and Management 147(2-3): 123–138.

Moeur, M. and Stage, A. R. 1995. Most Similar Neighbor: An improved sampling inference procedure for natural resources planning. Forest Science 41: 337–359.

Næsset E. 2002. Predicting forest stand characteristics with airborne scanning laser using apractical two-stage procedure and field data. Remote Sensing of Environment 80: 88–99.

Næsset, E. 2004. Practical large-scale forest stand inventory using a small-footprint airborne scanning laser. Scandinavian Journal of Forest Research 19: 164–179.

Næsset, E. 2007. Airborne laser scanning as a method in operational forest inventory: status of accuracy assessments accomplished in Scandinavia. Scandinavian Journal of Forest Research 22: 433–442.

Næsset, E., Gobakken, T., Holmgren, J., Hyyppä, H., Hyyppä, J., Maltamo, M., Nilsson, M., Olsson, H., Persson, Å. and Söderman, U. 2004. Laser scanning of forest resources: The Nordic experience. Scandinavian Journal of Forest Research 19: 482–499.

Oliva, J., Romeralo, C., and Stenlid, J. 2011. Accuracy of the Rotfinder instrument in detecting decay on Norway spruce (Picea abies) trees. Forest Ecology and Management 262(8): 1378–1386. doi:10.1016/j.foreco.2011.06.033.

Ørka, H.O., Næsset, E., and Bollandsås, O.M. 2009a. Classifying species of individual trees by intensity and structure features derived from airborne laser scanner data. Remote Sensing of Environment 113: 1163–1174.

Ørka, H.O., Næsset, E., and Bollandsås, O.M. 2009b. Comparing classification strategies for ALS tree species recognition. In Proceedings of Silvilaser 2009 - The 9th international conference on lidar applications for assessing forest ecosystems. Edited by S.C. Popescu, R. Nelson, K. Zhao & A. Neuenschwander, Texas A&M University, College Station, Texas, USA, pp. 46–53).

Osada, R., Funkhouser, T., Chazelle, B. and Dobkin, D. 2002. Shape distribution. ACM Transactions on Graphics 21: 807–832.

Packalén, P. and Maltamo, M. 2008. Estimation of species-specific diameter distributions using airborne laser scanning and aerial photographs. Canadian Journal of Forest Research 38: 1750–1760.

Packalén, P., Suvanto, A., and Maltamo, M. 2009. A two stage method to estimate species-specific growing stock. Photogrammetric Engineering and Remote Sensing 75: 1451–1460.

Packalén, P., Vauhkonen, J., Kallio, E., Peuhkurinen, J., Pitkänen, J., Pippuri, I. and Maltamo, M. 2011. Comparison of the spatial pattern of trees obtained by ALS based forest inventory techniques. In Proceedings of SilviLaser 2011, October 16–20, 2011, Hobart, Australia.

Pal, M. 2005. Random forest classifier for remote sensing classification. International Journal of Remote Sensing 26: 217–222.

Persson, Å., Holmgren, J. and Söderman, U. 2002. Detecting and measuring individual trees using an airborne laser scanner. Photogrammetric Engineering & Remote Sensing 68: 925–932.

Pesonen, A., Maltamo, M., Eerikäinen, K., and Packalèn, P. 2008. Airborne laser scanning-based prediction of coarse woody debris volumes in a conservation area. Forest Ecology and Management 255: 3288–3296.

Peuhkurinen, J., Maltamo, M., Malinen, J., Pitkänen, J. and Packalén, P. 2007. Preharvest measurement of marked stands using airborne laser scanning. Forest Science 53: 653–661.

Peuhkurinen, J., Mehtätalo, L. and Maltamo, M. 2011. Comparing individual tree detection and the area-based statistical approach for the retrieval of forest stand characteristics using airborne laser scanning in Scots pine stands. Canadian Journal of Forest Research 41: 583–598.

Pitkänen, J. 2005. A multi-scale method for segmentation of trees in aerial images. In Proceedings of the SNS-meeting at Sjusjøen – Forest Inventory and Planning in

Nordic Countries, Norway, September 6–8, 2004. Edited by K. Hobbelstad, NIJOS-report 09/05, Norwegian Institute of Land Inventory, Oslo, Norway.

Pitkänen, J., Maltamo, M., Hyyppä, J. and Yu, X. 2004. Adaptive methods for individual tree detection on airborne laser based canopy height model. In Proceedings of ISPRS working group VIII/2: "Laser-Scanners for Forest and Landscape Assessment". Edited by M. Theis, B. Koch, H. Spiecker, and H. Weinacker. University of Freiburg, Germany, pp. 187–191.

Pretzsch, H., Biper, P. and Durský, J. 2002. The single-tree based simulator SILVA: construction, application and evaluation. Forest Ecology and Management 162: 3–21.

Pudil, P., Novovicova, J., and Kittler, J. 1994. Floating search methods in feature selection. Pattern Recognition Letters 15: 1119–1125.

Reitberger, J., Heurich, M., and Krzystek, P. 2010. Estimation of stem volume by using 3D segments derived from full-waveform LiDAR data. In Proceedings of SilviLaser 2010, Freiburg, Germany, 14–17 September 2010.

Reynolds, M.R. Jr., Burk, T.E. and Huang, W.-C. 1988. Goodness-of-fit tests and model selection procedures for diameter distribution models. Forest Science 34: 373–399.

Schleyer A. 2001. Das Laserscan-DGM von Baden-Württemberg. In Reports on the Photogrammetric Week 2001, Stuttgart, Germany. Available from http://www.ifp.uni-stuttgart.de/publications/phowo01/Schleyer.pdf.

Siipilehto, J. 2006. Linear prediction application for modelling the relationships between large number of stand characteristics of Norway spruce stands. Silva Fennica 40(3): 517–530.

Spångberg, K., Arlinger, J., Wilhelmsson, L., Lundqvist, S-O., and Hedenberg, Ö. 2001. Taper functions for Picea abies (L.) Karst. and Pinus sylvestris L. in Sweden. Arbetsrapport 491. Skogforsk, Sweden.

Story, M., and Congalton, R.G. 1986. Accuracy assessment - a users perspective. Photogrammetric Engineering and Remote Sensing 52: 397–399.

Straub, C. and Koch, B. 2011. Estimating single tree stem volume of Pinus sylvestris using airborne laser scanner and multispectral line scanner data. Remote Sensing 3: 929–944, doi:10.3390/rs3050929.

Sundblad, L-G., Thor, M., Wilhelmsson, L., Linander, F. and Hannerz, M. 2008. Hjälpmedel för inventering av rotröta i stående skog. Resultat nr 18, 2002. Skogforsk, Sweden.

Tapio. 2007. Hyvän metsänhoidon suositukset. 100 p.

Valbuena, R., Mauro, F., Arjonilla, F.J., and Manzanera, J.A. 2011. Comparing airborne laser scanning-imagery fusion methods based on geometric accuracy in forested areas. Remote Sensing of Environment 115: 1942–1954.

Varnik, V. N. 1998. Statistical Learning Theory. John Wiley and Sons Inc.

Vauhkonen, J. 2010. Estimating crown base height for Scots pine by means of the 3-D geometry of airborne laser scanning data. International Journal of Remote Sensing 31(5): 1213–1226.

Vauhkonen, J., Ene, L., Gupta, S., Heinzel, J., Holmgren, J., Pitkänen, J., Solberg, S., Wang, Y., Weinacker, H., Hauglin, K.M., Lien, V., Packalén, P., Gobakken, T., Koch, B., Næsset, E., Tokola, T. and Maltamo, M. (in press). Comparative testing of single-tree detection algorithms under different types of forest. Forestry.

Vauhkonen, J., Korpela, I., Maltamo, M. and Tokola, T. 2010. Imputation of single-tree attributes using airborne laser scanning-based height, intensity, and alpha shape metrics. Remote Sensing of Environment 114: 1263–1276.

Vauhkonen, J., Packalén, P. and Pitkänen, J. 2011. Airborne laser scanning-based stem volume imputation in a managed, boreal forest area: a comparison of estimation units. In Proceedings of SilviLaser 2011, October 16–20, 2011, Hobart, Australia.

Venables, W.N. and Ripley, B.D. 2002. Modern Applied Statistics with S. New York: Springer.

Weinacker, H., Koch, B., Heyder, U., and Weinacker, R. 2004. Development of filtering, segmentation and modelling modules for LIDAR and multispectral data as a fundamental of an automatic forest inventory system. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences; ISPRS: Vienna, Austria, 2004, Volume 36, Part 8/W2, pp. 50–55.

Wilhelmsson, L., Arlinger, J., Spångberg, K., Lundqvist, S-O., Grahn, T., Hedenberg, Ö. and Olsson, L. 2002. Models for Predicting Wood Properties in Stems of Picea abies and Pinus sylvestris in Sweden. Scandinavian Journal of Forest Research 17(4): 330–350.

Yu, X., Hyyppä, J., Kaartinen, H., and Maltamo, M. 2004. Automatic detection of harvested trees and determination of forest growth using airborne laser scanning. Remote Sensing of Environment 90: 451–462.