The prediction of single-tree biomass, logging recoveries and quality attributes with laser scanning techniques

Ville Kankare
Department of Forest Sciences
Faculty of Agriculture and Forestry
University of Helsinki

Academic dissertation

To be presented with the permission of the Faculty of Agriculture and Forestry, University of Helsinki, for public criticism in the Walter Auditorium of the EE-building, Agnes Sjöbergin katu 2, Helsinki on June 5th, 2015 at 12 o'clock noon.

ABSTRACT

The precise knowledge of forest structural attributes, such as biomass, logging recoveries and quality of the available timber, play an essential role in decision-making, forest management procedure planning and in wood supply chain optimization. Remote sensing-aided mapping applications are used intensively to acquire required forest resource information. Laser scanning (LS) is one of the most promising remote sensing techniques, which can be used to estimate forest attributes at all levels, from single trees to global applications. The main objectives of the present thesis were to develop LS-based methodologies for mapping and measuring single trees. More specifically, new high-density LS-based models and methodologies were developed for the prediction of aboveground biomass (AGB), logging recovery, stem curve and external tree quality estimation. Multisource remote sensing methodologies were additionally introduced for the detailed next generation forest-inventory process. Substudies I and II concentrated on developing LS-based biomass models. Total AGB was estimated with the relative root mean squared errors (RMSE%) of 12.9% and 11.9% for Scots pine (*Pinus sylvestris* L.) and Norway spruce (*Picea abies* (L.) H.Karst.), respectively using terrestrial LS (TLS) -derived predictors in multiple regression modelling. TLS-based AGB models significantly improved the estimation accuracy of AGB components compared to state-of-the-art allometric biomass models. Airborne LS (ALS) resulted in slightly higher RMSE% values of 26.3% and 36.8% for Scots pine and Norway spruce compared to results obtained with TLS. The goal of substudies III and IV was to predict timber assortment and tree quality information using high-density LS data. Sawlog volumes were estimated with RMSE% of 17.5% and 16.8% with TLS and a combination of TLS and ALS, respectively. Tree quality is an important factor for accurate and successful timber assortment estimation. The use of TLS data showed high potential for tree quality assessment. Results in IV showed that trees could be successfully classified in different quality classes based on TLS-measured attributes with accuracies between 76.4% and 83.6% depending on the amount of quality classes. Substudies V and VI presented new automatic processing tools for TLS data and a multisource approach for the more detailed prediction of diameter distribution. Automatic processing of TLS data was demonstrated to be effective and accurate and could be utilized to make future TLS measurements more efficient. Accuracies of ~1 cm were achieved using the automatic stem curve procedure. The multisource single-tree inventory approach combined accurate treemaps produced automatically from the TLS data, and ALS individual tree detection technique for predicting forest preharvest information. Results from diverse forest conditions were promising, resulting in diameter prediction accuracies between 1.4 cm and 4.7 cm depending on tree density and main tree species. Each substudy (I–VI) presented new methods and results for single-tree AGB modelling, external tree quality classification, automatic stem reconstruction and multisource approaches.

4

ACKNOWLEDGEMENTS

LIST OF ORIGINAL ARTICLES

This thesis consists of an introductory review followed by 6 research articles. Articles I–V are reprinted with kind permission from the publishers, while article VI is a submitted manuscript.

I   Kankare V., Holopainen M., Vastaranta M., Puttonen E., Yu X., Hyyppä J., Vaaja M., Hyyppä H. & Alho P. (2013). Individual tree biomass estimation using terrestrial laser scanning. ISPRS Journal of Photogrammetry and Remote Sensing 75: 64–75.
http://dx.doi.org/10.1016/j.isprsjprs.2012.10.003

II   Kankare V., Räty M., Yu X., Holopainen M., Vastaranta M., Kantola T., Hyyppä J., Hyyppä H., Alho P. & Viitala R. (2013). Single tree biomass modelling using airborne laser scanning. ISPRS Journal of Photogrammetry and Remote Sensing 85: 66–73.
http://dx.doi.org/10.1016/j.isprsjprs.2013.08.008

III Kankare V., Vauhkonen J., Tanhuanpää T., Holopainen M., Vastaranta M., Joensuu M., Krooks A., Hyyppä J., Hyyppä H., Alho P., Viitala R. (2014). Accuracy in estimation of timber assortments and stem distribution −A comparison of airborne and terrestrial laser scanning techniques. ISPRS Journal of Photogrammetry and Remote Sensing 97: 89–97.
http://dx.doi.org/10.1016/j.isprsjprs.2014.08.008

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

V   Liang X., Kankare V., Yu X., Hyyppä J., Holopainen M. (2014). Automated Stem Curve Measurement Using Terrestrial Laser Scanning. IEEE Transactions on Geoscience and Remote Sensing 52: 1739–1748.
http://dx.doi.org/10.1109/TGRS.2013.2253783

VI   Kankare V., Liang X., Vastaranta M., Yu X., Holopainen M., Hyyppä J. (2015). Diameter distribution estimation with laser scanning based multisource single tree inventory. ISPRS Journal of Photogrammetry and Remote Sensing, submitted manuscript.

AUTHOR CONTRIBUTION

Ville Kankare was the main author of articles I, II, III, IV and VI. Ville Kankare was responsible for the main parts of the data processing, analysis, calculations, model development and accuracy evaluations in the respective articles. Xinlian Liang was the main author in article V and responsible for the development of the automatic processing algorithm and analysis. Eetu Puttonen and Xiaowei Yu were responsible for feature extraction in article I. Matti Vaaja with Ville Kankare was responsible for the TLS data collection for article I. Minna Räty was responsible for feature extraction and data matching in article II. Marianna Joensuu and Anssi Krooks were responsible for data acquisition along with Ville Kankare in articles III and IV. Ville Kankare was responsible for data collection, manual measurements and writing in article V, along with Xinlian Liang. Xinlian Liang was responsible for automatic data processing in article VI. All the articles were improved by the contributions of the co-authors at various stages of the planning, data collection, analysis and writing process.

Table of contents

ABBREVIATIONS

3D	3-dimensional
ABA	Area-based approach
AGB	Aboveground biomass
ALS	Airborne laser scanning
CHM	Canopy height model
D6	Diameter at a height of six meters
DBH	Diameter at breast height
DEM	Digital elevation model
DTM	Digital terrain model
DSM	Digital surface model
FI	Forest inventory
GPS	Global Positioning System
GNSS	Global Navigation Satellite System
IMU	Inertial measurement unit
ITD	Individual tree detection
LiDAR	Light detection and ranging
LS	Laser scanning
MLS	Mobile laser scanning
MS	Multisource
MS-STI	Multisource single-tree inventory
nDSM	Normalized digital surface model
NFI	National forest inventory
R^2	The coefficient of determination
RMSE	Root mean squared error
RS	Remote sensing
STI	Single-tree inventory
TALS	Combination of TLS and ALS
TCA	Tree cluster approach
TLS	Terrestrial laser scanning
UAV	Unmanned aerial vehicle
VOL	Stem volume

INTRODUCTION

Background

Finnish forest management practices have been based on intensive small-scale forestry because forests are mainly privately owned and the average size of forest holdings is relatively small (~ 25 ha). In other Nordic countries, e.g. in Sweden and Norway, the average size of forest holdings is also relatively small but larger than in Finland: 45-50 ha and 45 ha, respectively. The economic value (profitability) of forest holding relies on detailed and up-to-date information of forest structure and attributes (Holopainen et al. 2014). Accurate forest resource information is crucial to individual owners during decision-making, but also for forestry organizations, enabling effective forest resource management and wood supply optimization. Information on forest resource attributes, e.g. timber assortments, diameter distribution, tree quality, biomass distribution, bioenergy potential and yield value are required to support decision-making in sustainable forest management. The estimation of timber assortments and biomass have been based on modelling approaches because these attributes are costly to measure in the field.

Forest mapping over large areas has typically been based on generalizing field sample plot measurements using coarse- or medium-resolution remote sensing (RS) data and other numeric map data. Small-scale forest management practices cause mosaic-like forest structures. Forest mapping over such land use or vegetation patterns is challenging, especially using medium- or coarse-resolution RS data with pixel sizes varying from 30 m (e.g. Landsat 7) to 250 m (e.g. MODIS). Previous studies have shown that the miss-match between field measurement data, an individual pixel of satellite data (Lu 2006) and the scarcity of available field data (Hancock et al. 2012) are the main challenges in forest attribute estimation. Coarse pixel size in the RS data results in mixed pixels on stand boundaries, leading to a description loss of the vegetation structure variability especially when looking at relatively small areas (e.g. forest stands of 1−3 hectares or field-measured sample plots).

Forest resource information systems have advanced to a state where substand-level information can be utilized. For example, Finnish Forest Centres currently utilize an information system that is based on forest attribute maps with 16 m × 16 m resolution. Forest organizations benefit from more detailed forest resource information e.g. when allocating various forest management tasks and optimizing the flow of raw materials. Incomplete or inaccurate forest information leads to non-optimal forest management decisions and thus adds to the expenses (e.g. Holopainen et al. 2010). With accurate forest resource information, forests could be seen as standing storages of raw material, which could be harvested based on material demand.

The decisions and optimization of forest management tasks are often based on stand-level mean diameter, basal area, height or age, although the most significant attributes describing timber quality and log yield is the stem form and diameter distribution (Kilpeläinen et al. 2011; Uusitalo and Isotalo 2005; Uusitalo 1997). Stand-level forest resource information that has been used for management planning for years rarely includes information concerning stem form or tree quality, because these attributes cannot be measured cost-efficiently using traditional means. Stem form has been modelled using taper curve models (e.g. Laasasenaho

1982) with knowledge of tree species, diameters (diameter at breast height (DBH, 1.3 m) and diameter at 6 m (D6) and height. Errors in stem form predictions will cause inaccurate bucking simulations (Holopainen et al. 2010), which will affect the decision-making process.

Accurate knowledge concerning the quality of available timber is also essential when planning and managing the raw material flow from the forest to the end product. It significantly affects the total income amount from timber sales due to quality defects, where sawlog-sized trees can be degraded to pulpwood during the harvest. It is more profitable for the forest owner to grow high-quality timber when the demand and the pricing methods support the real added value. Widespread discussion has globally ensued in the forest industry concerning the possibility of modifying timber pricing more towards quality-based pricing (e.g. Malinen et al. 2010). This could significantly affect the timber market and also the accuracy and detail of required forest resource information (Figure 1).

Three-dimensional (3D) technologies for forest mapping and monitoring have been developed rapidly during the last decades. The capability to directly measure the 3D structure of forests has been the key turning point in forest mapping-related RS applications. Laser scanning (LS)-based techniques in particular have been studied immensely and some of these techniques have already come in to operational use.
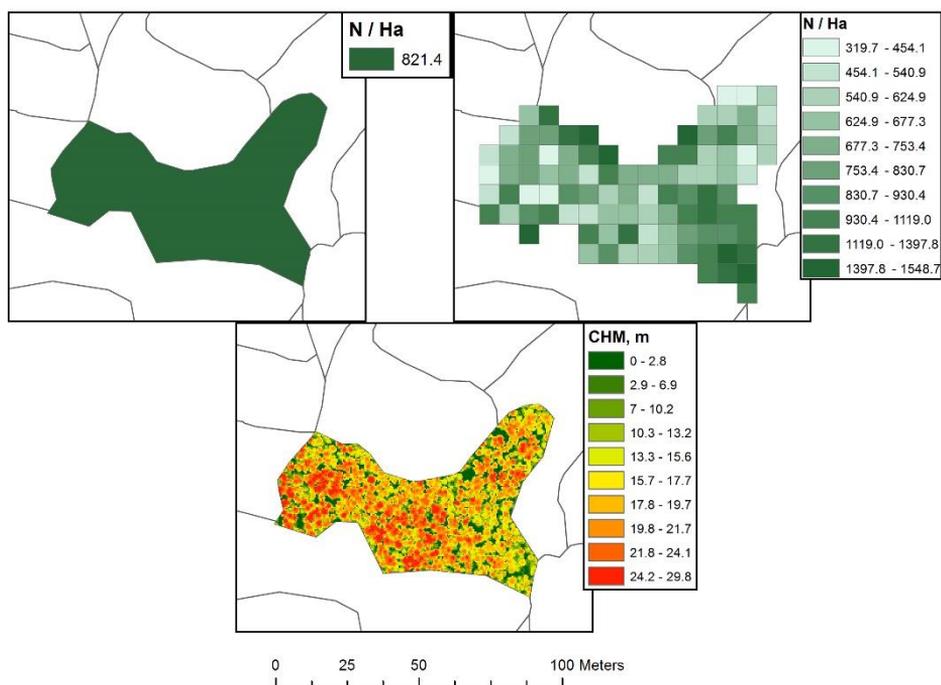
Figure 1. The different detail levels of forest inventory. The top-left corner shows the mean stem density value at stand-level; The top-right corner shows the predicted stem density value at 16 m x 16 m grid-level; The bottom picture shows the canopy height model from high-density airborne laser scanning data where single trees can be detected.

Airborne LS (ALS) is the most promising current laser scanning technique from the forest mapping and monitoring point of view because ALS data can be collected efficiently over large areas and forest attributes can be estimated accurately using detailed tree-by-tree measured modelling data. ALS has been used to estimate forest structural attributes from single trees (e.g. height, DBH and volume) to broader scales. Field measurements required in forest mapping over large areas are seen as costly to conduct especially if stem form, quality or biomass attributes are to be measured. For example, single-tree biomass cannot be measured in the field without destructive sampling and suitable allometric models are often not available. Fixed-position (mounted on a tripod) terrestrial laser scanners offer opportunities for the 3D mapping of smaller areas such as sample plots or individual trees with millimetre levels of detail. Terrestrial LS (TLS) is seen as an efficient and objective option for acquiring the required and accurate field data to be used, e.g. as a reference for forest mapping over large areas (Liang et al. 2011; Lindberg et al. 2012).

LS development has mainly focused on the estimation of stand- or plot-level forest attributes and the accuracies of the methods are rarely validated at single-tree-level. The requirement of more detailed information and more efficient data acquisition from the single-tree-level is growing. Single-tree methods have not yet been adopted for operational use due to the higher costs of data acquisition and more demanding data processing although the first single-tree methods were already presented in 1999 (see e.g. Hyyppä and Inkinen 1999).

Thesis objectives

The main aim of forest resource mapping is to produce unbiased and accurate information concerning forest structure and resources for forest owners, managers and the forest industry. The precise knowledge of the biomass (bioenergy potential), logging recoveries and the quality of the available timber at single-tree-level will play an essential role in the next generation of forest mapping systems. The main objectives of the present thesis were to develop methods for deriving single-tree-level attributes from active 3D RS data. LS-derived metrics were used in aboveground biomass (AGB) modelling in substudies I and II and the aim of substudies III and IV was to measure information on logging recoveries and external tree quality from harvesting sites using LS data. Substudy V presents an automatic stem curve measurement technique and substudy VI evaluates a multisource single-tree inventory (MS-STI) for predicting diameter distribution combining TLS and ALS. The following specific objectives were set for studies I–VI:

I   Determination of single-tree-level biomass requires accurate measurements of tree structure and properties, which cannot be acquired without destructive sampling with traditional field measurements. Our goal was to assess the accuracy of high-density 3D point clouds measured with TLS from standing trees in single-tree AGB estimation.

II   RS methods are increasingly used in practical forest resource mapping and monitoring but the single-tree-level attribute models are mainly developed based on traditional field measurements. Our objective was therefore to assess the

accuracy of ALS-derived metrics in single-tree-level AGB modelling for Scots pine (*Pinus sylvetstris* L.) and Norway spruce (*Picea abies* (L.) H.Karst.).

III   Detailed knowledge of timber assortments and diameter distributions are essential for efficient forest management and optimization of raw material flows. Our objective was to compare the accuracies of high-density LS techniques (ALS and TLS) when estimating stem diameters and both total and assortment volumes at single-tree-level. The study also demonstrated a multisource approach, where TLS and ALS techniques were combined for a more detailed mapping of single trees.

IV   The quality of the available timber is a critical factor when timber harvesting is planned and the wood supply chain is optimized. Our objective was to assess the accuracy of external tree quality classification based on tree-level attributes measured from TLS point clouds.

V   Stem bucking requires information on stem curve. Stem curve cannot be measured in detail with traditional measurements prior to cutting. Our main objective was to demonstrate the automatic and non-destructive measurement of stem curve using TLS point clouds.

VI   MS-STI is an approach for obtaining tree-level forest resource information. It is based on a high-detail treemap created, e.g. from TLS or harvester measurements, and lower resolution RS data, e.g. ALS or aerial images. The accuracy of diameter distribution prediction of the MS-STI approach was assessed in varying forest conditions using automatically produced TLS-based treemaps as a foundation of the method.

Laser scanning

Principles of airborne laser scanning

ALS is an active RS technique that uses the time-of-flight measurement principle to measure the distance to an object. The time-of-flight measurement utilizes the precise timing required for a pulse to travel from the sensor to the object and back to determine the range (Kukko 2013). ALS data are normally collected using a small airplane or helicopter. The measuring equipment includes a Global Navigations Satellite System (GNSS) and an inertial measurement unit (IMU). The GNSS provides the position and velocity while the IMU measures the orientation information based on accelerometers. It is possible to correct erroneous location measurements (e.g. gaps in GNSS data) using the IMU. With the known position of the sensor and precise orientation of these range measurements, the position (x, y, z) of an object is defined. The principle of ALS is presented in Figure 1.
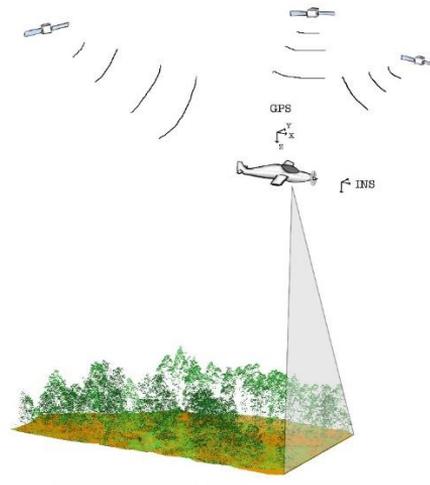
Figure 2. An airborne laser scanning (ALS) system includes a global position system (GPS) and an inertial measurement unit (IMU) for accurately measuring the position and orientation of the airplane. ALS uses the time-of-flight measurement principle to measure the distance to an object resulting in a three-dimensional point cloud (x, y, z) if combined with the GPS and IMU information.

ALS data acquisition and the resulting point cloud is highly affected by forest structure but also the specifications of the scanning system play an important role in how the laser pulse interacts with the forest. In the simplest case, a laser pulse scatters directly from the top of the dense canopy layer or from the ground, resulting in only a single return. Because the forest canopy is not a solid surface, the measurement scenario becomes more complex and may result in multiple returns. The transmitted pulse can pass through the top of the canopy and intercept with different parts of the canopy, such as the trunk, branches and foliage, before reaching the ground. Multiple returns are recorded in most cases (Figure 3), but some systems also record the full waveform of the reflected laser pulse. The first returns are mainly assumed to reflect from the top of the canopy and the last returns mainly from the ground.
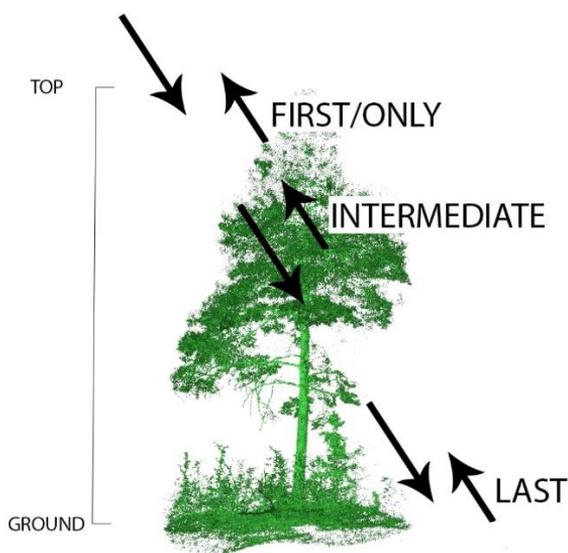
Figure 3. Laser pulse interaction with tree canopy can result in multiple returns because the forest canopy is not a solid surface. First returns are assumed to originate from the treetop and the last returns from the ground.

LS system specifications and configurations affect how the laser pulse interacts in the forest structure and how the spatial distribution of the returns will be determined. According to Ackermann (1999), laser pulse penetration is approximately 20–40% during the summer in European coniferous and deciduous forests. The penetration rate is higher during the winter, especially in deciduous forests. Ahokas et al. (2011) concluded that the penetration rate is between 20–50% in Finnish coniferous forests, depending mainly on forest structure and tree size (volume).

Data acquisition specifications affect laser pulse interaction in the forests, e.g. the ground returns decrease as the scanning angle increases (TopoSys 1996); a larger scan angle or higher flying altitude or speed will result in a smaller return density but larger spatial coverage (Lindberg 2012) and a higher flight altitude alters the distribution of laser returns from the top and within the tree canopies (Næsset 2004). From a practical point of view this is a challenge in LS-based forest inventory (FI) because ALS data will be collected using multiple sensors and varying data acquisition parameters due to the rapid development of the scanning technologies and also the changing objectives of the measurement campaigns. These variations in equipment and parameters is shown to affect forest attribute estimation (see e.g. Kankare et al. 2015; Næsset 2009) due to resulting dissimilarities in point cloud properties, which will cause variation on the point cloud-derived metrics (Næsset 2009).

Forest attribute estimation from ALS has been based on two main approaches: an area-based approach (ABA) (Næsset 2002; White et al. 2013) and individual tree detection (ITD (Hyyppä and Inkinen 1999). ABA relies on a statistical dependency between the field-measured forest attributes and the predictor metrics derived from the RS data. Forest mapping over larger areas using ABA is based on generalizing tree-by-tree measured field sample plots using low-density ALS data (< 1 point per m^2) but also higher density ALS data can be

used if available. ABA accuracy is highly affected by the amount, quality and distribution over different strata of the available training/modelling data and the resolution of the ALS data. In ITD, individual trees are recognized and segmented from the laser point cloud. Tree attributes are then determined either directly from the point cloud (e.g. height and crown width) or the attributes are estimated (e.g. DBH, volume and biomass) based on existing DBH, volume and biomass models. Single-tree attributes can also be modelled using point cloud metrics extracted for each tree segment, but this approach requires some amount of tree-level reference/modelling data. A method named the tree cluster approach (TCA) has been demonstrated in addition to these two approaches (e.g. Breidenbach et al. 2010). TCA can be seen as a combination of the two presented methods, where tree segments can include none, one or multiple trees and attributes are estimated based on statistical modelling.

Principles of terrestrial laser scanning in forest measuring

TLS is a 3D mapping approach of smaller areas with millimetre-level detail. TLS data are most often collected from fixed-positioned tripods within the target area. Targets surrounding the static measurement location are recorded as 3D points (x, y, z and intensity) reflected from the target surfaces visible to the scanner (see Figure 4). TLS distance measurement is based on either phase shift or time-of-flight measurements. The time-of-flight measurement principle is the same as that used in ALS, where the scanner uses the precise timing required for the pulse to travel from the sensor to the object and back for determining the range. Phase shift measurements utilize a continuous, phase modulated pulse and measure the phase of the returning pulse (e.g. Kukko 2013; Lindberg 2012). The phase information of the pulse can be used to calculate distance by recognizing the time when a pulse with a specific phase was emitted. The distance measurement accuracy in phase shift TLS is typically more accurate than time-of-flight TLS but the maximum range is shorter. Point density is highest near the scanner position and decreases rapidly as a function of distance. Average point density is approximately 25 000 points per m^2 (e.g. Leica HDS6100 with high resolution). A typical commercial TLS scanner rotates 180 degrees horizontally and 310 degrees vertically, providing full coverage of the surrounding area in a short time frame. The time required for a single scan with the above-mentioned resolution varies from approximately two to four minutes depending on the scanner in use.
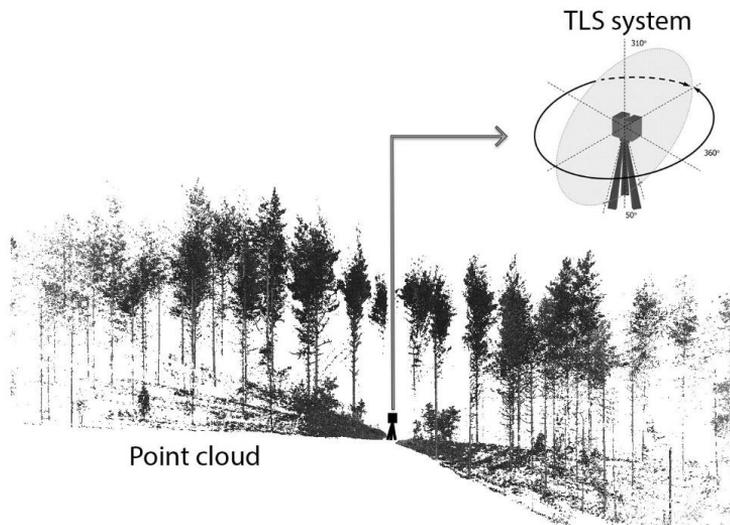
Figure 4. The principle of terrestrial laser scanning (TLS): TLS data are collected from a fixed-positioned tripod within the target area. A typical commercial TLS scanner rotates 180 degrees horizontally and 310 degrees vertically (top-right corner), providing full coverage of the surrounding area in a short time frame. A high-detail 3D point cloud (x, y, z, intensity) is recorded based on the emitted pulses reflected from the target surfaces visible to the scanner.

TLS data can be acquired from the sample plot using one or multiple scanning locations. Data acquisition is fast if only a single scanning location is used (e.g. Liang et al. 2012), but the resulting point cloud is incomplete in most cases because of shadowing effects, which cause challenges especially in tree detection and trunk modelling. The shadowing effect is caused particularly by different objects (e.g. trunk, branch or understorey vegetation) at close proximity to the scanner location. This effect is shown as data gaps behind the specific object in the point cloud (see Figure 5, left). Point density within the sample plot additionally varies considerably if the point cloud from only a single scan is used as shown in Figure 5 (left).

Multiple scans from a sample plot provides more detailed measurement data from the target area (as shown in Figure 5, right) where the shadowing effect is reduced, but this is a more labour-intensive approach (e.g. Holopainen et al. 2013; Yu et al. 2013). This approach utilizes a central scan with one or more additional scan locations divided around the target area to provide a comprehensive point cloud. Multiple scans can be accurately co-registered using artificial reference targets (spheres) distributed over the target area (see the Methodology section). Figure 5 demonstrates the differences between these single or multiple scan datasets. Liang and Hyyppä (2013) presented a new approach for co-registering multiple scan data, where no artificial reference targets are required and the co-registration is performed using automatically created stem location maps from each individual scan.
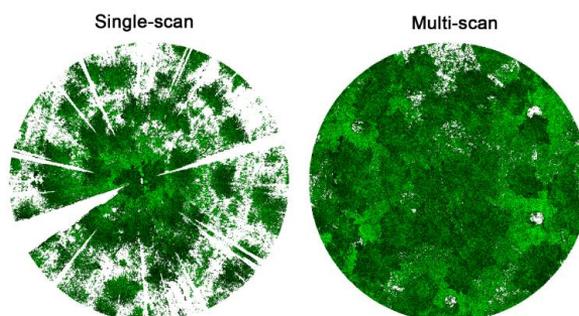
Figure 5. Example of TLS point clouds collected with one or multiple scans from the sample plot. The multiple scan approach significantly reduces the occlusion caused by tree stem, branches or other understorey vegetation near the scanner location.

TLS has been used in forestry for the detailed structure modelling of smaller areas (sample plots) and individual trees. TLS offers the means for determining basic tree attributes from sample plots, such as location, DBH and tree height directly from the point cloud. TLS additionally provides detailed measurement possibilities from standing trees (e.g. stem curve and branch distribution), which are not feasible to measure using traditional means. The prerequisite for TLS data usage is the automatic processing procedures, which have developed rapidly during the last few years (e.g. Liang 2013; Maas et al. 2008; Raumonen et al. 2013; Thies et al. 2004)**,** but these techniques have not yet been adopted into operational forest mapping.

Tree attribute estimation

Comparison of airborne and terrestrial laser scanning techniques

The possible applications and usability of the two LS techniques (ALS and TLS) differ significantly in forestry. The following chapters will compare these techniques in single-tree-level forest attribute estimation. The techniques differ e.g. in feasible area coverage, view perspective, resolution and forest attribute estimation procedure. Figure 6 demonstrates the difference between the resulting point clouds at single-tree-level for these two LS techniques. ALS can be applied in collecting wall-to-wall data (point clouds) over interest areas, as the spatial resolution of the data enables the detection of single trees. TLS on the other hand is more suitable for measuring millimeter-level information from individual trees or sample plots (e.g. typically 200–500 m^2). Previous studies on single-tree mapping with ALS and TLS have shown that tree detection algorithm, the tree attribute estimation procedure and forest structure are the most important factors in estimating tree attributes (Kaartinen et al. 2012b; Vauhkonen et al. 2012). Table 1 summarizes the two different laser scanning techniques.
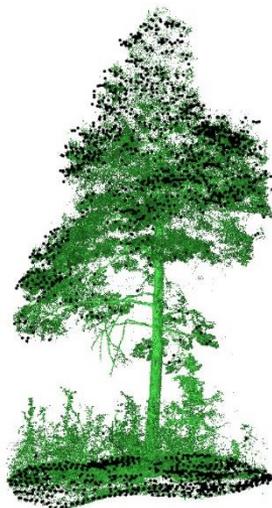
Figure 6. Point clouds from a single tree measured with ALS (black dots) and TLS (green dots).

Table 1. Summary of the ALS and TLS systems.

	ALS	TLS
View perspective	Airborne	Ground
Spatial coverage	Single tree to wall-to-wall coverage	Single tree to small area
Point density /m^2	0.5–20	25000[a]
Usability	Single tree to wall-to-wall coverage	Reference measurements
Forest attribute estimation		
DBH	Model	Direct[b]
Height	Direct	Direct[c]
Stem curve	Model	Direct[b]
Volume	Model	Model (based on stem curve)
Biomass	Model	Model
Data collection time	Fast	Slow
Platform	Aeroplane, helicopter	Tripod

[a] Leica HDS6100 scanner with high resolution

[b] Can be measured automatically from the data.

[c] Direct measurement of tree height is not possible in dense forest conditions with closed canopy layer due to the lack of visibility to the tree top.

Single-tree detection

The main distinction in tree detection between ALS and TLS is the difference between view perspectives. ALS data are collected from above the forest canopy looking down (Field of view typically varying from ±15–20 degrees) and TLS data are collected from below the canopy with a moving view angle (vertically from 25° to 335°). ITD from ALS data are most often based on detection of local maxima values and segmentation of the tree crown around the local maxima. Tree detection from TLS is based on stem point recognition and modelling underneath the canopy. Despite the differences in view perspectives, successful tree detection in both systems is highly dependent on forest structure (visibility) and the used processing algorithms (Kaartinen et al. 2012b; Liang 2013; Vauhkonen et al. 2012).

The emitted pulse density prerequisite for successful tree detection from ALS point clouds has been > 5 points/m^2 but a few studies have demonstrated that dominant layer trees can also be detected from lower density (~ 2 points/m^2) point clouds (e.g. Vastaranta et al. 2011; Yu et al. 2011). A pulse density increase from 2 points/m^2 to 8 points/m^2 was found to have only minimal effect on tree detection accuracy (Kaartinen et al. 2012b). The bottleneck of ALS-based tree detection have been the small non-dominant layer trees, which are not visible from the above canopy view perspective. Hyyppä and Inkinen (1999) showed that 40–50% of the single trees could successfully be segmented from the canopy height model (CHM) in coniferous forests. Persson et al. (2002) improved the tree detection rate to 71%. Yu et al. (2011) assessed the tree detection accuracy of various managed forest conditions, resulting in an overall accuracy of 69%. Kaartinen et al. (2012) and Vauhkonen et al. (2012) assessed the tree detection accuracies of international comparison studies where a total of 18 different ITD algorithms were tested. Studies demonstrated that the applied ITD algorithm and forest structure have a significant effect on ITD accuracy. In all, tree detection accuracies have varied between 25% and 100% (e.g. Kaartinen et al. 2012; Popescu et al. 2003; Vauhkonen et al. 2012; Yu et al. 2011) of the total number of trees, but e.g. Persson et al. (2002) and Vastaranta et al. (2011) demonstrated that 60.2–99.9% of the detected trees contributed 75.9–100% of the total volume in the study areas.

Compared to ALS, TLS is capable of also accurately detecting the non-dominant layer trees if data collection is performed using multiple scans in varying forest structures. The shadowing effect (visibility from the scan location) caused by the forest structure (tree stem, branches and other understorey vegetation) has a significant effect on tree detection accuracy. Tree detection accuracy is significantly higher if multiple scans are used in data collection, because data can also be obtained from areas that are occluded in a single scan. The most used method for tree detection from TLS point clouds has been to cut a horizontal cross-section (slice) from the data and recognize the tree stem by point clustering and circle fitting (see e.g. Lindberg et al. 2012; Maas et al. 2008; Moskal and Zheng 2012). Tree detection accuracy with multiple scans has previously varied between 91.7–100%, whereas with single-scan the corresponding accuracy has varied between 55.3–90%, depending on tree density in the study areas (Liang and Hyyppä, 2013; Liang et al. 2012; Maas et al. 2008). Liang and Hyyppä (2013) showed that similar tree detection accuracies can be achieved compared to the multiple scan approach where artificial targets are used in co-registration when using the multiple scans approach, where individual scans are co-registered using automatically generated stem location maps. The method introduced by Liang and Hyyppä

(2013) reduces the amount of equipment and work time required in the field during data collection.

Tree species, DBH, height and stem curve

Tree attributes can either be directly measured from the point cloud or modelled based on the metrics derived from the point clouds depending on the LS data used. ALS directly measures only tree height and possibly canopy structure (e.g. tree canopy width), while all other tree attributes (e.g. DBH and volume) have to be modelled. ALS tends to underestimate tree height (see e.g. Rönnholm et al. 2004) due to pulse interactions within the canopy. Rönnholm et al. (2004) showed that single tree height was underestimated, on average, by 0.76 m to 1.46 m depending on the tree species. Similar underestimations where found by Maltamo et al. (2004), where 46% of the trees were underestimated by > 1 m and 37.4% by < 1 m. Tree DBH can be modelled based on allometric relationship between DBH and height (see e.g. Kalliovirta and Tokola 2005). Existing models based on tree species, height, and DBH are also used when estimating stem volume and curve (see Laasasenaho 1982). Tree attributes can also be estimated using metrics describing tree shape and point distributions within the tree segment and ABA techniques (e.g. Maltamo et al. 2009; Vauhkonen et al. 2010; Yu et al. 2011). Estimation accuracies for DBH have varied between 1.25 cm and 3.9 cm, depending on the method (general model or locally calibrated model) and study area (e.g. Maltamo et al. 2009; Vauhkonen et al. 2013, 2010; Yu et al. 2011).

TLS enables direct measurement of most tree attributes that are typically collected in forest inventories, e.g. DBH, height, stem curve and quality attributes, such as the height of the lowest branch (see e.g. Kretschmer et al. 2013; Liang and Hyyppä 2013; Maas et al. 2008; Pfeifer and Winterhalder 2004; Raumonen et al. 2013). Tree volume can be calculated directly based on the stem curve by calculating the volume of 3D cylinders fitted to the stem points. The uncertainty caused by the modelling required in ALS is therefore reduced but the spatial coverage is not sufficient for wall-to-wall inventories. Stem curve measurements from TLS point clouds were first mentioned in Thies et al. (2004) and the most commonly used method is to fit cylinders to the stem points at predefined heights along the stem. Thies et al. (2004) demonstrated the use of cylinders fitted to the stem point clouds, but this method required initial starting on a stem surface to begin stem reconstruction. Maas et al. (2008) utilized tree location and horizontal slice to fit the circle into a 2D projection of the stem points. This procedure can be repeated at predefined heights to reconstruct the stem curve. Maas et al. (2008) reported that the largest errors in stem curve occurred at the bottom and top of the tree. The RMSE was 1.0 cm between the heights of 0.7 m and 7.70 m in Maas et al. (2008).

Tree height is also underestimated by TLS data because the highest point of the tree canopy is not visible to the scanner. Tree height accuracy compared to field measurements have varied between 1.36–6.53 m in previous studies (e.g. Liang and Hyyppä 2013; Maas et al. 2008). The accuracies of the DBH measurements from TLS data have varied between 0.74–3.25 cm depending on the data acquisition strategy (one or multiple scans)(e.g. Liang and Hyyppä 2013; Maas et al. 2008; Yao et al. 2011). Stem form has been shown to highly affect DBH (see e.g. Saarinen et al. 2014). Most of the automatic data processing methods with TLS utilize the above-mentioned cylinders fitted to the stem points, from which DBH is derived from the cylinder at a height of 1.3 m. This approach assumes that the stem form

is circular, which will cause uncertainty in the DBH estimates. DBH estimation accuracy should be further researched in more diverse forest condition because previous study sites have mainly exhibited plantation or managed forest conditions.

Tree species recognition has been a difficult task, which has not yet been fully solved. It was initially concluded that LS techniques are not solely sufficient for accurately recognizing tree species and complementary data sources were required (Vauhkonen et al. 2014). However, the focus has been on developing tree species recognition methods based on ALS data (see e.g. Holmgren et al. 2008; Korpela et al. 2010; Vauhkonen et al. 2010, 2009), while Puttonen et al. (2010b) have published results using TLS only. Tree species recognition in their study was conducted using a combination of TLS and a hyperspectral sensor. With ALS data, tree species classification is based on either the ABA approach, where tree species is predicted for the target area using accurate modelling data or ITD, where different types of metrics (e.g. structural, intensity or waveform) are used as a basis for the classification (see Vauhkonen et al. 2014)). One promising approach is to utilize complementary information derived from an MS approach with a combination of LS and spectral image data, which could be provided by multi- or hyperspectral sensors (Vauhkonen et al. 2014). Tree species classification accuracies for Scandinavian boreal forests, where the number of commercially important tree species is rather low, have varied between 60 % and 93% (see e.g. Holmgren and Persson 2004; Holmgren et al. 2008; Korpela et al. 2010; Vauhkonen et al. 2010, 2009).

Single-tree biomass

Single-tree AGB estimation based on LS techniques has not been widely studied previously due to the costly reference data required for modelling. AGB estimation relies on allometric models based on tree species, DBH and height if the models exist in the specific target area. Destructive sampling of single trees is necessary when developing new allometric models, used to derive the exact biomass of the tree components (stem, branches and leaves) as a reference. ABA accuracy has been the main focus in AGB estimation at the plot- or stand-level (e.g. Bortolot and Wynne 2005; Jochem et al. 2011; Kankare et al. 2013; Latifi et al. 2010; Næsset 2004; Popescu et al. 2004). The first results of single-tree-level AGB estimation based on ALS data were presented in Popescu (2007). Popescu's (2007) results showed that 78% of the variation associated with single-tree-level AGB was explained by linear models. Zhao et al. (2009) improved the R^2-value to 0.80 and 0.88 for pine and deciduous trees respectively, using the scale invariant approach. It should be noted that neither of these studies utilized destructive sampling as a reference while allometric model estimates were used as reference. Räty et al. (2011) and Hauglin et al. (2013b) were among the first to utilize destructive sampling as a basis for ALS AGB models. Hauglin et al. (2013b) developed models for single-tree branch biomass estimation for Norway spruce using either the random forest technique, stepwise or simple linear least squares regression. Estimation accuracies (relative root mean squared error, RMSE%) varied from 35% to 51% depending on the applied method.

Where ALS-based AGB estimation is based on either predicting species, DBH and height and then modelling the AGB or by modelling the AGB directly using point cloud-derived predictors, TLS enables AGB component estimation directly based on e.g. stem volume calculated from the automatic stem curve. Yu et al. (2013) demonstrated that stem

reconstruction and correspondingly derived stem volume can be used as explanatory variables for accurately modelling stem biomass. An RMSE of 17.3 kg (12.5%) was reported (Yu et al. 2013). A similar approach could also be utilized for branch biomass estimation if the automatic measurement of branches could be solved. A few promising approaches have already been demonstrated (see e.g. Raumonen et al. 2013). Hauglin et al. (2013a) demonstrated that more accurate branch biomass can be achieved using TLS than with existing allometric models. The RMSE of 32% of Norway spruces were found in the voxel-based approach. Based on the results achieved in Hauglin et al. (2013a), Hauglin et al. (2014) studied the use of TLS measurements as a reference for ALS-based branch biomass model development. They found only a small increase (3%) in the branch biomass accuracy if TLS is used in ALS model training compared to when branch biomass is estimated based on ALS-derived DBH and height with existing allometric models.

Logging recoveries and timber quality

The total volume of the stem and timber assortment (sawlog and pulpwood) volumes and their estimation accuracies have a critical impact on the decision-making and optimization of the raw material flow. Total volume estimation has been based on existing volume models (see e.g. Laasasenaho 1982) incorporating tree species, DBH and height as input attributes. Timber assortment volume or sawlog-% estimates have been based on measured mean attributes of the stand and on theoretical DBH distributions (e.g. the Weibull distribution (Bailey and Dell 1973)) of the study area (e.g. Maltamo and Gobakken 2014). Estimation accuracies have previously been reported mainly at the forest stand-level (m^3/ha) (Holmgren et al. 2012; Korhonen et al. 2008; Peuhkurinen et al. 2007). Although the studies by Peuhkurinen et al. (2007) and Holmgren et al. (2012) aggregated these estimates from individual tree segments, sawlog and pulpwood proportions have rarely been validated at the tree-level in previous studies. Vastaranta et al. (2014) demonstrated the use of MS-STI in the logging recovery estimation of a mature Scots pine stand where harvester measurements were used as a reference. The accuracy of sawlog volume prediction varied between 28.7–43.5% and pulpwood volume between 125.1–134.3% if either high or low density ALS or digital stereo imagery was used in the prediction. The variation was much smaller at stand level, resulting in a 0.2% difference at best (Vastaranta et al. 2014).

  LS techniques also enable the measurement of various external quality attributes, such as stem curve and lean, branch size, bark characteristics or canopy-related attributes. The capabilities to measure these attributes with ALS or TLS vary due to the different view perspective and amount of detail (point density) that can be extracted. ALS can be mainly used to measure different canopy or single-tree crown properties, such as canopy width or living crown density or height. No direct measurements of the tree trunk or branches can be obtained from ALS point clouds. ABA is a viable option for ALS-based quality estimation if the training data includes quality attributes (see e.g. Maltamo et al. 2009). TLS offers more possibilities for measuring quality attributes directly from single trees but with smaller spatial coverage. TLS has been successfully used to measure branch size distribution (Raumonen et al. 2013), stem form (taper, sweep and lean) (Pfeifer and Winterhalder 2004; Thies et al. 2004) and bark characteristics (see Kretschmer et al, 2013). Stängle et al. (2014) also demonstrated that external bark quality attributes can be linked with the internal quality of logs, as determined with strong correlation by X-ray computer tomography.

MATERIALS

Study areas and field measurements

The two study areas of this thesis are located at Evo (61.19ºN, 25.11ºE) and Hyytiälä (61.845° N, 24.287° E) (Figure 7). Both areas belong to the southern boreal forest zone and are comprised of a broad mixture of forest stands, varying from natural to intensively managed forests.

Extensive field measurement campaigns were carried out at Evo during 2007–2009. The study area consists of over 700 fixed-sized (300 m^2) circular sample plots established during this time window. Sampling the field plots was based on the prestratification of existing stand inventory data to distribute plots over various site types, tree species and stand development classes (see detailed description from Kankare et al. (2013)). The following tree attributes were measured for all trees with DBH > 5 cm: tree species, DBH, height and canopy layer (dominant or sub). Total volume and component AGB (total, stem, living or dead branch) were estimated using existing models based on species, DBH and height (Laasasenaho 1982; Repola 2009, 2008).

From these 700 previously established sample plots, 27 were selected for the TLS campaign in 2010. The selection criteria indicated that the plots should be as heterogeneous as possible. A total of 38 sample trees were selected within nine TLS campaign plots for substudies I, II and V. These 38 sample trees were measured in detail using destructive sampling. The following attributes were recorded: species, height, DBH, AGB components (total, stem, living and dead branch) and stem curve. In addition to the 38 sample trees measured from Evo, 26 sample trees were measured using the same procedure from Hyytiälä in 2010 and 2011. These were used as additional trees in substudy I. Substudy VI utilized the full 27 sample plot dataset measured with TLS in 2010.

Field measurements of the forest stands used in substudies III and IV were acquired in 2012 from Evo. The stand was approximately 2 ha in size and the main tree species was Scots pine. The following attributes were measured for the 144 sample trees within the stand: location, species, height, DBH, D6, external quality class and height of the lowest living and dead branches. Tree quality was recorded by ocular assessment based on instructions by the National Forest Inventory (NFI) of Finland. Table 2 summarizes the field measurements and available laser scanning datasets.

Harvester data was acquired from the above-mentioned stand in autumn 2012. The logging machine was a Ponsse Beaver and it gathered STM data according to the Standard for Forest Data and Communication (StanFord 2009). An STM file includes data for each felled tree regarding the logging machine's position at the time of felling, stem diameters at 10-cm intervals from the felling height to the final bucking height, tree species, bucking parameters and bucked assortment volumes. The following attributes were utilized in substudy V: DBH, sawlog and pulpwood volume and bucking information.
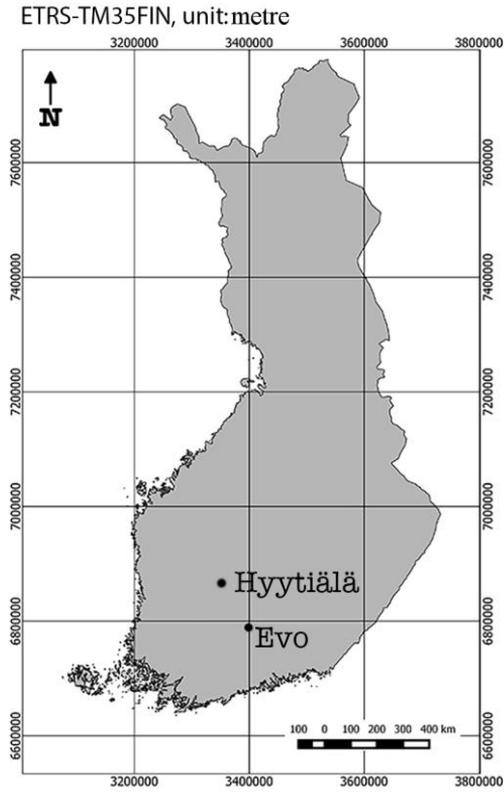
Figure 7. Study areas were located at Evo (61.19⁰N, 25.11⁰E) and Hyytiälä (61.845° N, 24.287° E).

Table 2. Summary of the applied field datasets and the available laser scanning datasets.

Study	Area	Number of sample trees	Number of Field plots (area)	Number or stands (area)	ALS	TLS
I	Evo and Hyytiälä	64	-	-	No	Yes
II	Evo	38	-	-	Yes	No
III	Evo	144	-	1	No	Yes
IV	Evo	144	-	1	Yes	Yes
V	Evo	28	9	-	No	Yes
VI	Evo	579	27	-	Yes	Yes

Table 3. Summary of the applied ALS datasets and scanning parameters.

Acquisition date / Year	Area	Instrument	Altitude, AGL	Pulse density	Substudy
2009	Evo	Leica ALS50-II	568.3	10	II, VI
2011	Evo	Leica ALS50-II	1000	9	IV, V

Table 4. Summary of the used TLS datasets.

Acquisition date / Year	Area	Instrument	Single- or Multiscan mode	Substudy
2010	Evo	Leica HDS6100	Multi	I, III, VI
2010	Hyytiälä	Leica HDS6100	Multi	I
2012	Evo	Leica HDS6100	Multi	IV, V

Laser scanning

Airborne laser scanning

The ALS datasets used in this thesis were acquired in 2009 and 2011. The ALS datasets acquired in 2009 and 2011 were collected by Finnmap Ltd. and Terratec Ltd., respectively. Detailed information of the ALS campaigns is presented in Table 3.

Terrestrial laser scanning

Terrestrial laser scanning datasets were measured from sample trees, plots and stands in 2010 and 2012. A Leica HDS6100 scanner was used in all the measurement campaigns. TLS measurements were collected with multiple scans to ensure the best possible point coverage of the study area in question. A summary of the used TLS datasets is presented in Table 4.

METHODOLOGY – OVERVIEW

Airborne laser scanning data processing

Creation of terrain, surface and canopy height models

Digital elevation models (DEMs) are created by utilizing the echo type information recorded during data acquisition in addition to the x, y, z and intensity values. A digital terrain model (DTM, Figure 8 left) is created utilizing the lowest returns with pixel size, e.g. 1 m.
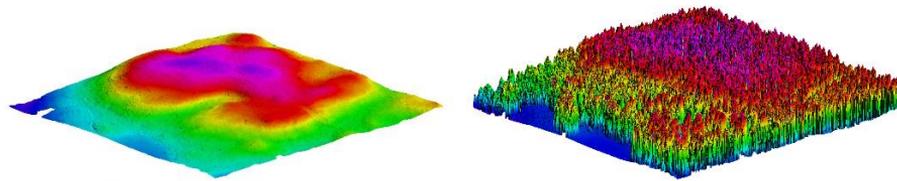
Figure 8. Digital terrain model (DTM, left) describes the ground elevation (above sea-level) with a spatial resolution e.g. 1 m. Canopy height model (CHM) describes the height of the aboveground vegetation with a spatial resolution e.g. between 0.25 m and 1 m.

Points belonging to the ground are generally classified by the ALS data provider (for more details in ground classification algorithms, see e.g. Sithole and Vosselman 2004). A digital surface model (DSM) is then created from the highest returns with pixel size varying from 0.25 m to 1 m depending on ALS data density. Values for empty pixels are interpolated based on the neighbouring pixel values (e.g. using fill gaps function in Terrascan software). A canopy height model (CHM, Figure 8 right) or a normalized digital surface model (nDSM) is calculated by subtracting DTM from DSM. ALS data tends to underestimate tree height (e.g. Hyyppä and Inkinen 1999) because the highest returns are often not reflected from the exact top of the tree but from the highest parts of the tree canopy. DTM accuracy also affects tree height underestimation. In forest conditions DTM accuracy varies between 10–50 cm (Axelsson 2000; Hyyppä et al. 2005; Kraus and Pfeifer 1998). DTM can be overestimated due to dense ground level vegetation, which causes CHM underestimation. Full-waveform ALS data could be utilized to improve the DTM classification accuracy (see e.g. Ullrich et al. 2007).

Individual tree detection

The initial task of ITD is to recognize single trees from the point cloud or created CHM (Figure 9). A wide variety of methods have been developed during the last decade for this purpose (see summaries from Kaartinen et al. (2012) and Vauhkonen et al. (2012)). A typical approach is to detect local maxima values (treetops) from the smoothed CHM. CHM is smoothed to filter out small variations on the crown surface. The amount of smoothing should be adjusted accordingly to the various forest structures; a high amount of smoothing will reduce the number of discovered maxima values (trees), which can e.g. (1) cause underestimation (commission trees) in recognized treetops in dense canopy layers or (2) reduce overestimation (omission trees) in recognized treetops in sparse canopy layers. After local maxima's are recognized, the boundaries of the treetops are segmented, e.g. using watershed segmentation.

ITD accuracy is shown to be dependent on pulse density and forest structure. The best ITD results can be achieved with higher pulse densities; the pulse density prerequisite for ITD has been > 5 pulses per m^2 but older trees with larger canopies can be recognized with lower pulse densities. It is possible to record the location, height and also crown shape for each tree using ITD.
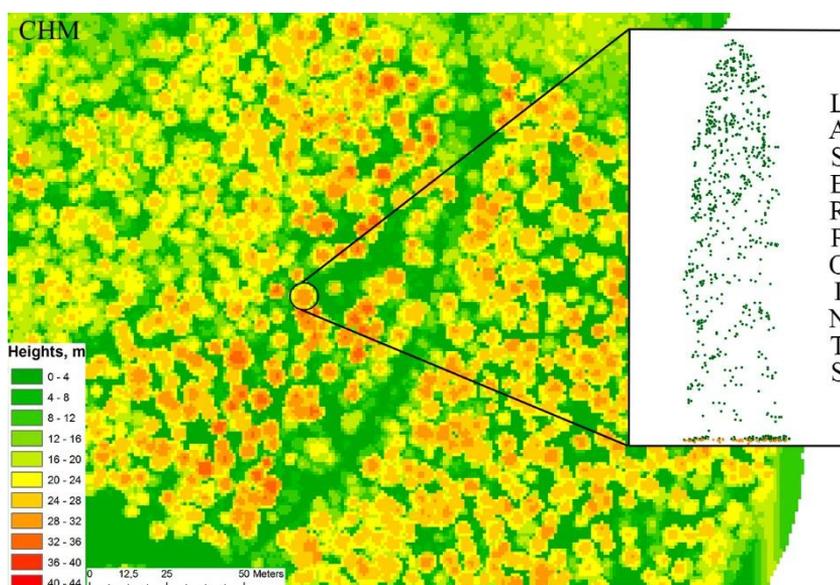
Figure 9. Example of the canopy height model (CHM) with a spatial resolution of 0.5 m and single tree points (right) extracted from high-density (emitted pulse density 10 points/m^2) airborne laser scanning (ALS) data.

Tree location is recorded from the location of the highest return inside each canopy segment or as an arithmetic mean of all returns inside the segment. Tree height is extracted from the highest return or from the highest CHM pixel value within the canopy segment. The created canopy segments can also be used to extract the returns belonging to single trees for further processing. Tree DBH is modelled based on the dependencies between tree height and DBH (Kalliovirta and Tokola 2005) and tree volume using the volume models of Laasasenaho (1982).

Predictor extraction from the point cloud for tree attribute modelling

The derived metrics describing the distribution of the point returns within each crown segment and the shape of the crown can be used e.g. in tree attribute modelling (see e.g. Korhonen et al. 2008; Næsset 2002). To minimize the effect of ground vegetation and rocks, returns close to zero m are typically considered ground returns and returns with a height greater than 2 m as vegetation returns (Yu et al. 2011). Metrics used in the modelling are then extracted only from the vegetation returns.

The following metrics were utilized in ALS-based single-tree AGB model development and single-tree attribute estimations: minimum, maximum, mean and standard deviation of the return heights. Penetration describes the relative amount of returns coming from ground level compared to all of the returns. Canopy height distribution percentiles describe a number of returns occurring from specific height percentiles (5th, 10th, 20th, …, 90th and 95th). Crown

density is extracted for corresponding percentiles as a portion of vegetation returns compared to all returns. Geometric metrics included attributes that describe canopy shape and size, e.g. canopy height, crown area, crown volume and maximum crown diameter.

Terrestrial laser scanning data processing

Point cloud registrations

All of the TLS datasets acquired in the substudies utilized multiple scans. This approach requires the co-registration of individual scans to create one unified point cloud from each study subject. Co-registration is based on the detection of reference targets from each point cloud. The reference targets are typically divided within the study area so that all reference targets are visible from the centre scan and a minimum of three from the remaining scans. Constant size spheres are fitted in the point clouds (detected reference targets) during the co-registration process. Based on the spheres, 3D transformation is calculated between the point clouds. Co-registration can be performed in an internal coordinate system, where each scan is registered to the coordinate system of the centre scan, or in an external coordinate system. An external coordinate system requires location measurements for the reference targets and scanning locations using the GNSS.

Manual tree detection and extraction

ITD and point cloud extraction was performed manually, with the same principle as an automatic approach utilizing the 3D environment. TLS point clouds were processed in scan groups (co-registered groups), which were searched from the sample trees using visual interpretation (Figure 10). The process is based on the detection of circular objects from a horizontal cross-section of each point cloud. Individual trees were detected and marked within the cross-section (see Figure 10) and location and tree attributes (e.g. DBH and height) were recorded. TLS returns belonging to each sample tree were also extracted for further processing and metric extraction using classification tools in Terrascan software.
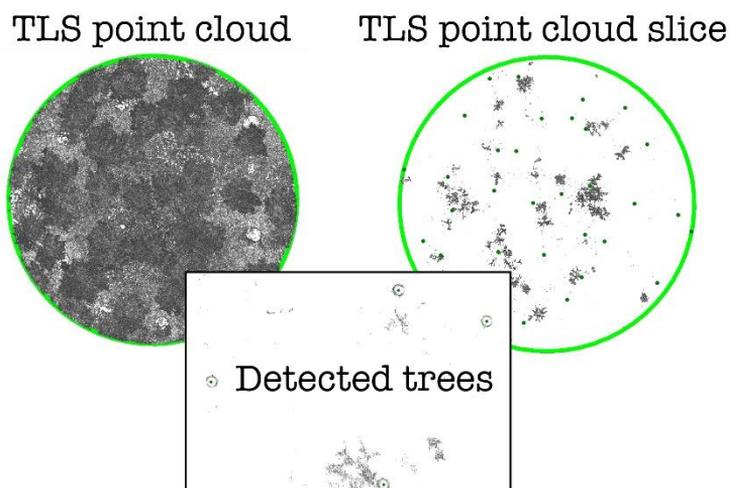
Figure 10. Individual tree extraction. Picture modified from Saarinen et al. (2014, p. 1037). The top left figure demonstrates the full point cloud within the sample plot. The top right figure demonstrates the horizontal cross-section taken at a height of 1.3 m and the bottom figure demonstrates the visible stem points as circular shapes while detected trees are marked with green dots.

Metric extraction

Similar statistical and geometrical metrics describing the canopy structure and point distributions were extracted from the TLS and ALS point clouds for tree attribute modelling purposes (see e.g. Puttonen et al. (2011, 2010) and Næsset and Gobakken (2005)). Statistical metrics included the minimum, mean and maximum height of the returns, point density within a specified fraction of the tree, percentiles calculated from 10% to 100% of the canopy height distribution, point densities in these same percentiles and also the skewness and kurtosis of the height distribution. The geometric metrics included crown height, perimeter and area, tree surface area and volume. The crown perimeter and area were calculated using 2D Delaunay triangulation and tree surface area and volume with 3D Delaunay triangulation.

Automatic measurements

Trees were detected and stem points were automatically recognized and reconstructed using a robust modelling procedure (described in detail in Liang and Hyyppä 2013; Liang 2013; Liang et al. 2012). Stem points were identified based on the spatial properties of the points. A local coordinate system was created for each point and the point was included as a stem surface point if neighbouring points were mainly distributed along two axes in the created coordinate system and the point's normal direction is roughly horizontal.

Stem curve modelling is based on the points recognized as stem points. A series of 3D cylinders is fitted to the selected points using robust estimation. This is used to weight the selected point to reduce the effect of cross errors (e.g. incorrectly selected stem points originating from the branches). Robust estimation is an important part of the modelling process, especially with Norway spruce where the branch point effect is more significant. The matching process is repeated as long as there are enough stem points. The stem curve model is further smoothed to reduce the possible cross errors. Smoothing is performed if the next cylinder estimation has a larger diameter than the average of *n* previous estimations. The value of *n* was set to 3 in substudy V. The diameters are extracted from the predefined heights along the stem based on the created 3D stem curve models. Stem volume was also computed as the sum of each stem section volume. Tree location is recorded from breast height along with the DBH measurement value.

Multisource approach

The multisource (MS) approach utilizes the attributes and metrics derived from TLS and ALS and could provide the means for more detailed analysis for single-tree mapping. MS approaches presented here utilized (1) a combination of TLS and ALS measurements and (2) TLS as auxiliary information for tree mapping where tree attributes are then estimated based on ALS ITD. Both methods rely on the high location accuracy of single trees.

The first approach combined trees manually detected from TLS and ALS point clouds by utilizing field-measured location information. With this approach, the direct measurements of the single-tree point clouds were utilized in tree attribute measurements in the following way: TLS was used for the detailed measurement of the tree stems and ALS for the height measurements. With this method it is possible to minimize the tree attribute modelling effect, which has been compulsory especially with ALS when *DBH* or volume is estimated.

The latter MS-STI approach is based on a detailed treemap produced with TLS or with mobile laser scanning (MLS) in the future. Two major bottlenecks of state-of-the-art ITD techniques used with ALS can be avoided using this method: (1) the detection of smaller, non-dominant layer trees and (2) tree species detection. MS-STI uses treemaps with location and tree species information from each tree as auxiliary information when deriving ALS metrics for ABA computations. The treemap is combined to ALS-based single-tree segments using location information. If two or more trees are within one ALS tree segment, the segment is divided equally to represent each tree. After the combination process, ALS-based metrics are derived and used in ABA estimation.

Results evaluation

The accuracies of the tree-level measurements and estimated attributes were evaluated by calculating the bias and RMSE:

$$Bias = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n} \qquad (1)$$

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

where n is the number of observations, y_i the value estimated for observation i and $\hat{y}_i$ the predicted value for observation i. Quality classification accuracy is presented in substudy IV as the relative error between the estimated and reference quality class. The goodness of fit of the diameter distributions were assessed in substudy VI using error indices suggested by Packalén and Maltamo (2008):

$$e = \sum_{i=1}^{k} 0.5 \left| \frac{f_i}{N} - \frac{\hat{f}_i}{\hat{N}} \right|, \tag{3}$$

where f_i is the true and $\hat{f}_i$ the predicted stem number in class i, k the number of classes or bins and N the true and $\hat{N}$ the predicted stem number of all diameter classes. Frequency differences are multiplied by 0.5 to scale the error indices between 0 and 1, 0 meaning a perfect fit and 1 meaning that the distributions do not overlap at all.

RESULTS AND DISCUSSION OF THE SUBSTUDIES

Individual tree biomass estimation using terrestrial laser scanning

The reliability of ground measured single-tree AGB information is vital to obtain accurate and unbiased AGB estimates over large areas. It is not feasible to measure tree-level biomass in the field because it requires destructive sampling, which will increase field measurement costs. Tree-level biomass models are therefore essential. Tree-level AGB can currently be estimated using species-specific models based on tree attributes that are easy to measure in the field (e.g. stem diameter and height). Frequently the limiting factor for these AGB models is that they can only be applied to certain geographical areas and also for a rather small number of tree species. These models are also mostly incapable of utilizing any attributes from the tree canopy, and therefore the canopy biomass accuracy in particular has been lower. Approximately 75–85% of the AGB of mature trees in the boreal forest zone is located in the tree stem (Lehtonen et al. 2004) and the amount of biomass related to the tree canopy is thus rather small (Figure 11). However, canopy biomass is important for the forest bioenergy sector, where logging residues, i.e. branches and treetops, is one of the main bioenergy raw material sources originating from forests. TLS has been used for the detailed modelling of small areas, e.g. sample plots (Liang 2013) and it could provide the means for measuring the acquired reference data from standing trees for biomass modelling. Substudy I presented the first TLS metrics-based AGB models available in the literature.
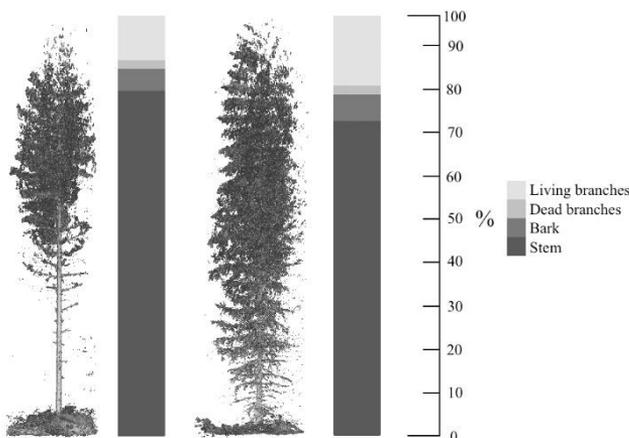
Figure 11. An example of terrestrial laser scanning point clouds of Scots pine (left) and Norway spruce (right) and their AGB distribution between different parts of the tree (stem, bark and branches). AGB distributions were calculated from the field measured sample trees.

The accuracy of AGB component estimation (total, stem, living and dead branch) increased significantly when multiple predictors where extracted from the TLS point cloud and used in the predicative models. The used predictors described the shape, size and statistical distribution of the points belonging to each sample tree. RMSEs for total, stem, living and dead branch estimation were 12.9%, 15.0%, 23.4% and 31.1% for Scot pine and 11.9%, 16.4%, 38.1% and 122.2% for Norway spruce were achieved, respectively. Corresponding accuracies for the allometric models (species, DBH, height, Repola 2009) were 21.6%, 29.5%, 62.1% and 132.1% for Scots pine and 29.6%, 34.7%, 101.1% and 182.1% for Norway spruce. Results showed that canopy biomass accuracy particularly can be improved with TLS-derived information. The most important metrics in the biomass modelling were stem volume and canopy shape and volume metrics. Dead branches were the most inaccurate AGB component because their amount is relatively small and the distinction between living and dead branches would require spectral information, which was not available. The ability to manually measure the stem curve from the TLS point cloud was also assessed in substudy I. The results showed that diameter can be measured accurately for the lower part of the tree. For the upper part of the tree the success rate of measuring the diameter decreased rapidly, especially for Norway spruce. The average success rates for measuring the diameter for Scots pine and Norway spruce were 86.9% and 48.2%, respectively.

Single-tree biomass modelling using airborne laser scanning

ALS methods are becoming a standard technique used in forest resource mapping and monitoring. The cost of ALS data acquisition campaigns is already fairly low (approximately 0.5–1 €/ha) for lower pulse density data (< 2 pts/m^2). Higher pulse density required for ITD is still more expensive but could bring added value to forest mapping especially in difficult

to reach areas. Vastaranta et al. (2012) introduced a forest mapping technique where the required reference data for large scale ABA estimation was measured using ITD. The accuracy of this method is highly dependent on the ability to model tree-level attributes based on ALS metrics. However, AGB models are developed mainly based on traditional field measurements. The main objective of substudy II was therefore to assess the accuracy of ALS- derived metrics in AGB modelling. Based on the modelling results of substudy I, the amount of predictor variables was minimized to create more simple models and dead branch biomass was assessed as part of the canopy biomass. ALS is capable of capturing variations in (1) tree height, (2) canopy size and (3) canopy density. The metrics used as predictor variables were therefore classified into these three classes and one metric from each class was selected as a final predictor variable in the developed regression models.

The RMSEs achieved with developed ALS-based AGB models for total, stem, canopy and living branch biomass were 26.3%, 28.4%, 30.2% and 32.6% for Scots pine and 36.8%, 27.6%, 77.8% and 70.8% for Norway spruce, respectively. Existing AGB models (Repola 2009, 2008) with field measured DBH and height resulted in more accurate AGB estimates. The only exception to this were the canopy and living branch biomass estimation accuracies for Norway spruce, were ALS-based models were slightly more accurate. The performance of the existing AGB models with ALS-derived DBH and height was also assessed to compare whether new ALS-based models can improve estimation accuracies. AGB estimation accuracy was lower for all the AGB components compared to developed ALS-based AGB models. These results support the assumption that new forest attribute models, especially for AGB components, should be developed based on the ALS technique and not only based on field measurements. However, developing robust ALS-based biomass models is challenging because it requires large treewise reference data measured with destructive sampling and ALS-derived metrics should be non-dependent on the data acquisition parameters.

Accuracy in estimation of timber assortments and stem distribution – A comparison of airborne and terrestrial laser scanning techniques

The economic value and detailed information on forest structure and possible timber quantities are crucial to individual owners and forestry organizations, thus enabling sustainable forest management operations. The information currently available for this purpose are the stand-level mean characteristics (e.g. basal area, stem density, volume and height), which lose information from the structure variability (see Figure 1). Timber assortments, diameter distribution, quality and yield value are the most essential factors for forest owners during decision-making concerning forest management operations and for forest organizations e.g. when searching for potential harvesting sites and optimizing raw material flows. The objective of substudy III was to compare high-density LS techniques for estimating stem diameters and assortment volumes. The study also presented an approach based on a combination of ALS and TLS (TALS) for more detailed forest mapping. Diameter distribution was predicted using DBH measurements from the TLS and harvester and DBH modelling results from ALS. Field measurements were used as reference for the DBH estimates. Timber assortment volumes were estimated using stem curve models and validated using harvester measurements.

The results showed that accurate tree-level timber assortment volume and diameter distribution estimations can be achieved using TLS and TALS. The RMSEs for sawlog volumes were 14.4%, 17.5%, 16.8% and 34.7% for field measurements, TLS, TALS and ALS, respectively. Field measurements were the most accurate but TLS and TALS were nearly as accurate. The accuracy of TLS-based methods can still be improved because the diameter measurements were performed manually and the comprehensive stem curve was not measured. Existing stem curve models were utilized along with the TLS because the automatic data processing was unavailable at the time and it is not feasible to manually measure stem curves from the point clouds for each single-tree. Results in substudy V confirmed that the accuracy of stem curve measurements can be improved using automated processing algorithm.

Tree quality was found to significantly affect the timber assortment volume estimations. The measurement included 11 trees, of which part of the sawlog-sized trunks were degraded to pulpwood. The pulpwood volume accuracy (RMSE%) was 108.5%, 110.9%, 110.4% and 109.1% for field measurements, TLS, TALS and ALS, respectively. The effect of quality was taken into account by removing these quality outliers and the pulpwood accuracies were significantly improved. The corresponding RMSEs were 57.6%, 60.1%, 59.3% and 57.1%.

The TALS combination method could be an interesting option for more detailed single-tree mapping, because the method reduces the amount of required modelling and the most important tree attributes (DBH, height and stem curve) can be measured directly from the point clouds. The biggest challenge is the location accuracy of each dataset, which should be resolved before this approach can be fully utilized in operational forestry.
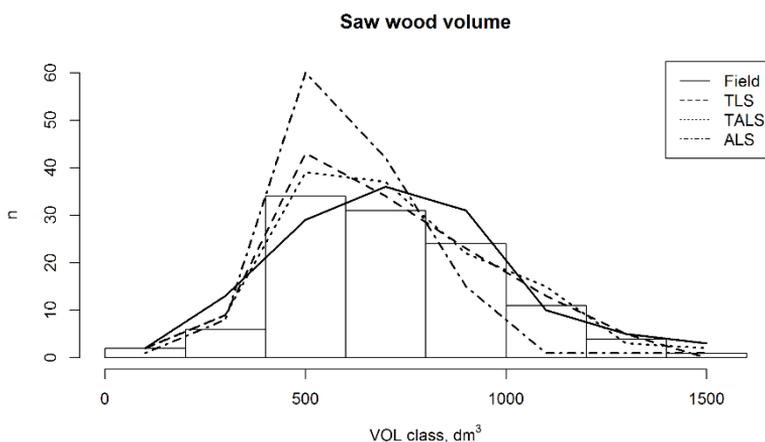

Figure 12. The saw wood volume distribution of a harvester (bars), field measurements (line), TLS measurements (dashed line), TALS measurements (dotted line) and ALS (dashed/dotted line). The x-axis presents the saw wood volume classed in 200 dm^3 intervals and the y-axis (n) present the number of trees belonging to specific saw wood volume class.

Estimation of timber quality of Scots pine with terrestrial laser scanning

Timber quality is an essential attribute to wood procurement planning in addition to available timber quantities because the technical quality of standing timber affects the production potential and possible raw material value. Scots pine quality is of particular interest in the Nordic countries, due to the strong association between quality and product recovery. The most influential quality attribute has been the distribution and size of the dead branches along the stem (e.g. Uusitalo 1997). Tree quality attributes are currently not included in preharvest information due to the high costs of the required fieldwork. The objective of substudy IV was to assess the accuracy of external quality attributes measured from TLS and the classification of trees according to three to five different quality categories. Results were compared to the quality classification conducted in the field by ocular assessment using the guidelines of the NFI of Finland.

The RMSEs for tree quality attributes, the lowest living and dead branches were 9.6% and 42.9%, respectively. The high measurement error for the lowest dead branch was caused by the shadowing effect in the point cloud data. The study stand was partly covered with dense understorey spruce layers, which caused gaps in the point cloud data, especially in the lower parts of the stems. The quality classification accuracies were promising despite this lower accuracy in the dead branch measurement. The trees were classified into three operationally important quality classes (high-quality timber, timber and pulpwood) with accuracies of 95.0% and 83.6% based on field- or TLS-measured tree attributes, respectively. The classification accuracies were slightly decreased if the amount of quality classes was increased to the five classes used in NFI. Respective overall accuracies were 87.1% and 76.4%.

TLS accuracies could be improved by minimizing the shadowing effect in data acquisition and by measuring more detailed quality attributes utilizing automatic stem, canopy shape and branch modelling. This would include automatic stem form measurements and canopy shape (e.g. volume and maximum diameter) and branch size distribution, which could be measured from the point cloud. Further development is therefore needed but tree quality information could bring additional value for preharvest measurements based on LS techniques.

Automated stem curve measurement using terrestrial laser scanning

The automatic processing of the TLS point cloud is of high interest and a prerequisite for bringing TLS-based techniques to operational forest mapping. The amount of TLS-collected data is substantial and data processing should be as fluent as possible. Stem curve is one of the most important tree attributes affecting the timber assortment accuracy as well as tree quality estimations. The goal of substudy V was to develop and demonstrate automatic and noninvasive stem curve measurements from TLS point clouds. This accuracy was compared to widely used stem curve models (Laasasenaho 1982) and manual measurements of the TLS point cloud.

The results showed that stem curve and volume can be measured accurately using the developed automatic procedure. The DBH measurement accuracies for automatic and manual

measurements were 8.2 mm and 12.6 mm, respectively. The RMSE of stem curve was 11.3 mm for automatic measurements and 10.3 for manual measurements. The manual measurements were thus less capable of measuring the diameter of the upper tree sections. Automated stem curve measurements could measure diameters up to 65.8% and 61.0% of the total height of Scots pine and Norway spruce, respectively. Corresponding values for manual measurements were 47.1% and 27.8%. Figure 13 presents the automatic stem curve model for a Scots pine tree.

The automatically measured stem curve allows the direct calculation of stem volume using the fitted 3D cylinders. An overall RMSE of 9.47% (29.29 dm^3) was achieved using automatic stem curve as a basis for volume calculation. Existing volume models (Laasasenaho 1982) with field-measured DBH, height and D6 resulted in a similar accuracy and in a slightly lower accuracy with DBH and height (appr. 1.1% lower), respectively. Substudy V demonstrated that stem curve and volume can be measured automatically and with high accuracy. Accurate and automatic stem curve measurements can be utilized as a basis of timber assortment volume and quality estimations but also in stem biomass modelling.
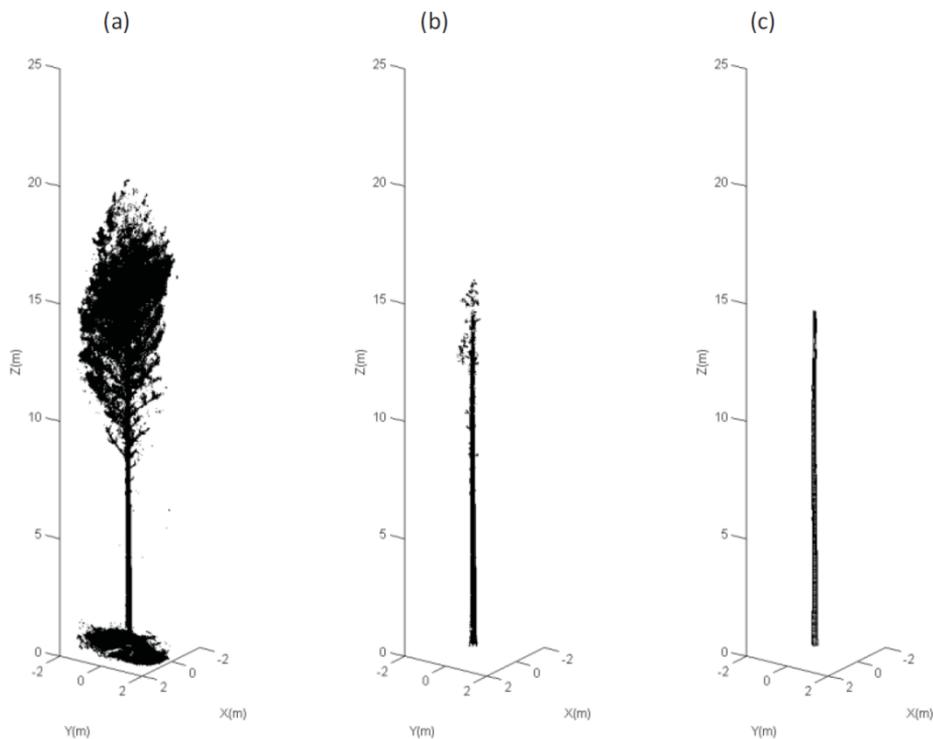

Figure 13. Stem curve modelling of a Scots pine tree. (a) Original point cloud, (b) recognized stem points and (c) automatically reconstructed stem curve model.

Diameter distribution estimation with laser scanning-based multisource single-tree inventory

State-of-the-art ALS techniques in single-tree-level forest mapping have two major issues that have currently not been fully solved: (1) the detection of non-dominant (small) layer trees and (2) tree species recognition. The objective of substudy VI was to demonstrate the use of the MS-STI technique, originally introduced by Vastaranta et al. (2014) and Saarinen et al. (2014), for predicting the diameter distribution in various forest conditions. MS-STI reduces the effect of two ITD-based issues mentioned beforehand. The method relies on accurate treemaps measured e.g. with TLS, MLS or a harvester. Here the required treemaps were produced using automatic TLS data processing. Automatic data processing and DBH measurement were also validated in varying forest conditions. The study was conducted using 27 sample plots from which TLS data was collected (see the Materials section).

An automatic processing algorithm of the TLS point cloud data detected and matched 71.2% of the reference trees within the sample plots. Tree detection and matching accuracies were highest (87.1%) in old-growth sample plots ready for final felling if tree density was considered. If the reference data was stratified by the main tree species of the sample plots, the highest detection and matching accuracies were found in Norway spruce-dominated (77.0%) or mixed (77.3%) sample plots. The overall accuracy (RMSE) of DBH of the matched trees was 42.5 mm. Within the data, 8 outlier trees were detected where DBH was significantly overestimated due to data matching errors, tree grouping or noise proximal to the tree trunks. The DBH RMSE was improved by 11.4% to 16.7 mm by removing these outlier measurements. The highest DBH measurement accuracies were found in mature forests (tree densities between 500 and 900 trees/ha). DBH was highest in deciduous trees-dominated or mixed sample plots if the main tree species was taken into account. Results show that both tree detection and matching and DBH measurement accuracy are highly dependent on forest structure. RMSE values were slightly lower or at similar level than reported in previous studies, but substudy VI presents the first results of TLS tree detection and DBH measurements in diverse forest conditions.

MS-STI proved an accurate and efficient method for DBH and diameter distribution estimation. The overall accuracy (RMSE) of DBH was 36.9 mm. Results showed that DBH accuracy decreased if tree density (trees/ha) increases. Highest accuracies were found in old-growth forests (tree densities less than 500/ha, Figure 14). MS-STI resulted in the best accuracies in Norway spruce-dominated forests (RMSE of 29.9 mm). The fit of predicted diameter distributions were assessed by calculating error indices suggested in Packalén and Maltamo (2008). The used error indices compare the true and the predicted stem number in a specific classes. Error indices are scaled between 0 and 1, 0 meaning a perfect fit and 1 meaning that the distributions do not overlap at all. Both methods, MS-STI and automatic TLS measurements, performed well, resulting in error indices of 0.11 and 0.06, respectively. Compared to the error indices reported in Packalén and Maltamo (2008), results in substudy VI were slightly better. Vastaranta et al. (2014) reported similar error indices of 0.10, 0.11 and 0.15 depending on the used datasets, although the method was tested in a single Scots pine-dominated stand with 144 sample trees. Results in VI were therefore promising, especially due to the more diverse forest conditions.

The challenge of the MS-STI approach is the combination of TLS-and ALS-detected trees due to the different view perspective (ground or air). The automatic segmentation of single trees from ALS point clouds was combined with TLS-detected trees using location information in the present study. If two or more trees were found inside a single ALS segment, the segment was equally divided. Features calculated from the divided segments might not describe the tree characteristics as well as the automatically extracted segments. The possibility of using modified TCA (Breidenbach et al. 2010) could therefore be a vital option for the MS-STI approach in the future. The possibility of creating a new TLS-aided ALS segmentation process should also be considered.
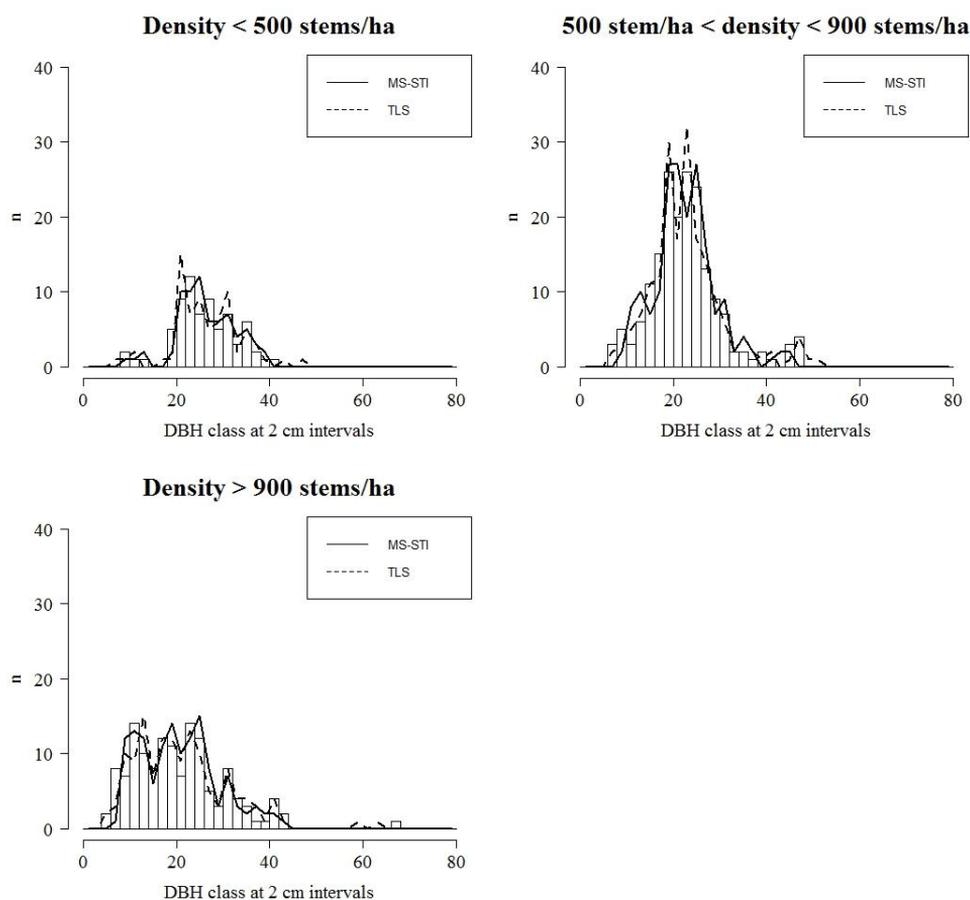

Figure 14. DBH distribution stratified by the tree densities of the sample plots.

CONCLUSIONS

Forest resource mapping, management planning and decision-making relies on the precise knowledge of forest structural attributes, such as biomass, logging recoveries and quality of the available timber. Accurate and unbiased forest resource information also plays an essential role in forest organizations when planning and optimizing wood supply chains and the flow of raw materials from the forest to the end product. A typical approach in the forest mapping of large areas has been based on generalizing field sample plot measurements using coarse- or medium-resolution RS. The coarse resolution of the RS data will cause challenges in forest attribute estimation especially in smaller target areas. Forest resource information systems have currently advanced to a state where substand-level information can be used. However, decision-making is still mainly based on stand-level mean attributes, in which a great deal of information concerning forest structure variability is lost as shown in Figure 1. The requirement for more detailed forest resource information especially at single-tree-level is growing, particularly from more mature stands where the added value is the highest.

Traditional field measurements at single-tree-level are costly to acquire, especially if tree quality, biomass and timber assortments are considered. These attributes have therefore been estimated using existing models and easily measurable tree attributes (tree species, DBH and height). The drawback to this approach is that the models might not exist in the target area or the existing models are site-specific causing estimation uncertainties. For example Kalliovirta and Tokola (2005) developed DBH models for Scots pine, Norway spruce and birch by dividing Finland into four regions, to which model parameters were estimated separately.

The use of 3D RS techniques, especially LS techniques, have revolutionized forest mapping applications in the past 15 years. The use of high-density 3D LS systems could open new possibilities for measuring and modelling single-tree attributes accurately and more efficiently. The focus of LS development has mainly been on stand- or plot-level forest attribute estimation and the method accuracies are rarely validated at single-tree-level. Single-tree methods have not been adopted to operational use due to the higher costs of data acquisition and more demanding data processing. Challenges in data processing have included e.g. the lack of automatic processing tools, tree species recognition and tree detection accuracy.

The main objectives of the present thesis were to develop active 3D RS methodologies for single-tree-level forest mapping. In the six different substudies (I–VI)

- novel methods to model single-tree AGB using TLS-and ALS-derived metrics were demonstrated,
- the accuracy of logging recovery estimation using high-density LS techniques and MS approach was assessed,
- the first results on external tree quality classification from harvesting sites using TLS data were presented,
- an automatic stem curve measurement technique from a TLS point cloud was demonstrated and validated against manual point cloud measurements and accurate field-measured reference and

- the accuracy of the MS-STI methodology was assessed in diverse forest conditions.

Current AGB models are mainly based on DBH, height and tree species information and do not utilize canopy size information, which could particularly improve canopy biomass estimation accuracies. AGB model development has also mainly been based only on field measurements without utilizing any RS data. Substudies I and II therefore concentrated on assessing the accuracy of LS-derived metrics in AGB modelling. Total AGB was estimated with an RMSE% of 12.9% and 11.9% for Scots pine and Norway spruce, respectively using TLS. TLS-based biomass models significantly improved the accuracy of component-level AGB estimation compared to existing biomass models. Based on these results we suggest the use of stem curve and crown size geometric features in AGB estimation rather than statistical 3D point metrics due to the dependency of statistical 3D metrics on various scanning parameters. Srinivasan et al. (2014) confirmed this suggestion and found the highest correlations from geometric features derived from TLS point clouds.

ALS resulted in slightly lower RMSE%-values of 26.3% and 36.8% for the same tree species compared to the acquired results with TLS. The developed ALS models improved the accuracy for estimating all Scots pine biomass components and total and stem biomass of Norway spruce, compared to existing biomass models with ALS-derived DBH and height. The achieved results were encouraging but further development is required due to the high dependency of the derived metrics and the scanning parameters. In all, ALS-based AGB models would provide the means for estimating AGB biomass from areas that are difficult to reach. An interesting option for future development would be to combine TLS and ALS at the single-tree-level, where the required reference would be measured using TLS and wall-to-wall estimation would be carried out with ALS.

The goal of substudies III and IV was to predict timber assortment volumes and tree quality information using high-density LS data. Results showed that accurate tree-level timber assortment volumes can be achieved using TLS or TALS, especially for the accurate estimation of log volume. Sawlog volumes were estimated with RMSE% of 17.5% and 16.8% with TLS and TALS, respectively. ALS resulted in the lowest estimation accuracies for DBH and the timber assortments, because DBH estimation in the ALS technique relies on developed DBH models. The TALS combination method is therefore an interesting option for more detailed tree mapping. TALS combines direct tree stem measurements from TLS and the more accurate tree canopy height measurements from ALS. With this combination, tree attributes can also be predicted for larger areas. The biggest challenge of TALS is the location accuracy of each dataset. This should be resolved before such MS approaches can be fully utilized in operational forestry.

Tree quality highly influenced timber assortment estimation accuracy in substudy III, where sawlog-sized tree sections were degraded to pulpwood by quality defects. Tree quality attributes were successfully measured in substudy IV and the trees were classified into different operationally important quality classes with high accuracy. Quality classification accuracies varied between 76.4–83.6% depending on the amount of quality classes. Based on the results of substudies III and IV, we suggest the development of a new bucking method founded on TLS data that can utilize detailed stem curves measurements and various quality features, e.g. branch distribution along the trunk.

Substudies V and VI presented new automatic processing tools for TLS data and the MS approach for a more detailed prediction of single-tree attributes. Automatic processing of TLS data was demonstrated to be effective and accurate and could be utilized to make TLS

measurements more efficient in the future. Accuracies of ~ 1 cm were achieved with the automatic stem curve procedure for Scots pine and Norway spruce trees. The automatic stem curve algorithm was able to measure a higher number of diameters than manual measurements. Manual measurement was difficult to conduct especially in the upper parts of the sample trees.

The automatic processing algorithm of TLS point cloud data are crucial if TLS and MS-STI are to be used in operational forest mapping. The automatic method applied in substudy VI performed accurately in the diverse forest conditions. The method detected and matched 71.7% of the reference trees within the sample plots. The overall DBH accuracy (RMSE) of the matched trees was 16.7 mm. Results showed that both tree detection, matching and DBH measurement accuracy are highly dependent on forest structure. Further testing with larger datasets is still required to confirm and further assess the effect of the processing algorithm and forest structure on the measurement accuracies.

MS-STI proved an accurate and efficient method for DBH estimation and for predicting diameter distribution. DBH estimation accuracies varied between 1.4–4.7 cm depending on tree density and main tree species with an overall DBH accuracy (RMSE) of 36.9 mm. Results showed that DBH accuracy decreased if tree density (trees/ha) increases. The highest accuracies were found in old-growth forests (tree densities less than 500/ha, Figure 14). MS-STI resulted in the best accuracies in Norway spruce-dominated forests (RMSE of 29.9 mm). Diameter distributions were predicted with low error indices resulting in a good fit compared to the reference. Based on results from our study and Saarinen et al. (2014), diameter distribution estimation with MS-STI is highly dependent on forest structure and the accuracy of the used treemaps. The most important development step for the MS-STI and automatic measurements of TLS point clouds is to develop tree species recognition methods and further develop tree detection techniques. The possibility of using MLS or harvester data as a basis for the required treemaps should also be assessed in the future.

This thesis developed methods for detailed single-tree-level forest mapping using high-density LS techniques. The substudies presented new and novel methods and results for single-tree AGB modelling, external tree quality classification, automatic stem reconstruction and MS approaches. Achieved results indicated that high-density LS techniques and MS approaches are a vital option for predicting the following single-tree-level attributes: (1) tree biomass, (2) timber assortments, (3) external tree quality, (4) stem curve and (5) diameter distribution. Technological development has taken major leaps towards more operational platforms in recent years by introducing new TLS technology combined with digital photography to provide colour (RGB) information to the point clouds, MLS (see e.g. Kukko 2013) platform, unmanned aerial vehicle (UAV), hyperspectral laser (see e.g. Puttonen et al. 2010) etc., which could be used in further developing the presented methods and especially tree species recognition. The results achieved in the substudies were promising but the suggested methodologies warrant further development and the validation if these techniques could be used in operational forest mapping. Important research subjects in the near future include: (1) to develop tree species recognition method based on LS techniques or MS approach, (2) to resolve the challenges in data matching in MS application, (3) to further develop automatic data processing of TLS point clouds to enable automatic measurements of external tree quality and study the link between external and internal tree quality measured in saw mills, (4) to further develop robust LS-based AGB models utilizing

automatically derived tree size and volume attributes from LS data with tree species-specific wood density and (5) to test the developed methods in the new data acquisition platforms (e.g. MLS and UAV data). The costs of the high-density data and equipment are constantly decreasing, enabling more efficient and higher detail data acquisition. New technologies, such as MLS, UAV and high resolution photogrammetry will provide new possibilities for MS-based forest mapping. In the forest resource system of the next generation, single-tree-level information will play an important role, especially in more mature forests where the added value of more detailed information is the highest.

REFERENCES

Ackermann F. (1999). Airborne laser scanning – Present status and future expectations. ISPRS Journal of Photogrammetry and Remote Sensing 54: 64–67. http://dx.doi.org/10.1016/S0924-2716(99)00009-X

Ahokas E., Hyyppä J., Yu X., Holopainen M. (2011). Transmittance of Airborne Laser Scanning Pulses for Boreal Forest Elevation Modeling. Remote Sensing 3: 1365–1379. http://dx.doi.org/10.3390/rs3071365

Axelsson P. (2000). DEM generation from laser scanner data using adaptive TIN models. International Archives of Photogrammetry and Remote Sensinging 33, 110–117.

Bailey R., Dell T. (1973). Quantifying Diameter Distributions with the Weibull Function. Forest Science 19: 97–104.

Bortolot Z.J., Wynne R.H. (2005). Estimating forest biomass using small footprint LiDAR data: An individual tree-based approach that incorporates training data. ISPRS Journal of Photogrammetry and Remote Sensing 59: 342–360. http://dx.doi.org/10.1016/j.isprsjprs.2005.07.001

Breidenbach J., Næsset E., Lien V., Gobakken T., 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. http://dx.doi.org/10.1016/j.rse.2009.12.004

Hancock S., Lewis P., Foster M., Disney M., Muller J.-P. (2012). Measuring forests with dual wavelength lidar: A simulation study over topography. Agricultural and Forest Meteorology 161: 123–133. http://dx.doi.org/10.1016/j.agrformet.2012.03.014

Hauglin M., Astrup R., Gobakken T., Næsset E. (2013a). Estimating single-tree branch biomass of Norway spruce with terrestrial laser scanning using voxel-based and crown dimension features. Scandinavian Journal of Forest Research 28: 456–469. http://dx.doi.org/10.1016/j.isprsjprs.2013.02.013

Hauglin M., Dibdiakova J., Gobakken T., Næsset E. (2013b). Estimating single-tree branch biomass of Norway spruce by airborne laser scanning. ISPRS Journal of Photogrammetry and Remote Sensing 79: 147–156. http://dx.doi.org/10.1016/j.isprsjprs.2013.02.013

Hauglin M., Gobakken T., Astrup R., Ene L., Næsset E. (2014). Estimating Single-Tree Crown Biomass of Norway Spruce by Airborne Laser Scanning: A Comparison of

Methods with and without the Use of Terrestrial Laser Scanning to Obtain the Ground Reference Data. Forests 5: 384–403.
http://dx.doi.org/10.3390/f5030384

Holmgren J., Persson Å. (2004). Identifying species of individual trees using airborne laser scanner. Remote Sensing of Environment 90: 415–423.
http://dx.doi.org/10.1016/S0034-4257(03)00140-8

Holmgren J., Persson Å., Söderman, U. (2008). Species indentification of individual trees by conbining high resolution LiDAR data with multi-spectral images. International Journal of Remote Sensing 29: 1537–1552.
http://dx.doi.org/10.1080/01431160701736471

Holmgren J., Barth A., Larsson H., Olsson, H., 2012. Combining Airborne Laser Scanning and Measurements from Harvesters. Silva Fennica 46, 227–239.
http://dx.doi.org/10.14214/sf.56

Holopainen M., Kankare V., Vastaranta M., Liang X., Lin Y., Vaaja M., Yu X., Hyyppä J., Hyyppä H., Kaartinen H., Kukko A., Tanhuanpää T., Alho P. (2013). Tree mapping using airborne, terrestrial and mobile laser scanning - A case study in a heterogeneous urban forest. Urban Forestry & Urban Greening 12: 546–553.
http://dx.doi.org/10.1016/j.ufug.2013.06.002

Holopainen M., Vastaranta M., Hyyppä J. (2014). Outlook for the Next Generation's Precision Forestry in Finland. Forests 5: 1682–1694.
http://dx.doi.org/10.3390/f5071682

Holopainen M., Vastaranta M., Rasinmäki J., Kalliovirta J., Mäkinen A., Haapanen R., Melkas T., Yu X., Hyyppä J. (2010). Uncertainty in timber assortment estimates predicted from forest inventory data. European Journal of Forest Research 129: 1131–1142.
http://dx.doi.org/10.1007/s10342-010-0401-4

Hyyppä J., Inkinen M. (1999). Detecting and estimating attributes for single trees using laser scanner. Photogrammetric Journal of Finland 16: 27–42.

Hyyppä H., Yu X., Hyyppä J., Kaartinen H., Kaasalainen S., Honkavaara E., Rönnholm P. (2005). Factors affecting the quality of DTM generation in forested areas. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36 (3/W19), 85-90.

Jochem A., Hollaus M., Rutzinger M., Höfle B. (2011). Estimation of aboveground biomass in alpine forests: a semi-empirical approach considering canopy transparency derived from airborne LiDAR data. Sensors 11: 278–295.
http://dx.doi.org/10.3390/s110100278

Kaartinen H., Hyyppä J., Yu X., Vastaranta M., Hyyppä H., Kukko A., Holopainen M., Heipke C., Hirschmugl M., Morsdorf F., Næsset E., Pitkänen J., Popescu S., Solberg S., Wolf B.M., Wu J.-C. (2012). An International Comparison of Individual Tree Detection and Extraction Using Airborne Laser Scanning. Remote Sensing 4: 950–974.
http://dx.doi.org/10.3390/rs4040950

Kalliovirta J., Tokola T. (2005). Functions for estimating stem diameter and tree age using tree height, crown width and existing stand database information. Silva Fennica 39: 227–248.
http://dx.doi.org/10.14214/sf.386

Kankare V., Vastaranta M., Holopainen M., Räty M., Yu X., Hyyppä J., Hyyppä H., Alho P., Viitala R. (2013). Retrieval of forest aboveground biomass and stem volume with airborne scanning LiDAR. Remote Sensing 5: 2257–2274. http://dx.doi.org/10.3390/rs5052257

Kankare V., Vauhkonen J., Holopainen M., Vastaranta M., Hyyppä J., Hyyppä H., Alho P. (2015). Sparse density, leaf-off airborne laser scanning data in aboveground biomass component prediction. Forests in press.

Kilpeläinen H., Lindblad J., Heräjärvi H., Verkasalo E. (2011). Saw Log Recovery and Stem Quality of Birch from Thinnings in Southern Finland. Silva Fennica 45: 267–282. http://dx.doi.org/10.14214/sf.117

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

Korpela I., Ørka H.O., Maltamo M., Tokola T. (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. http://dx.doi.org/10.14214/sf.156

Kraus K., Pfeifer N. (1998). Determination of terrain models in wooded areas with airborne laser scanner data. ISPRS Journal of Photogrammetry and Remote Sensing 53: 193–203. http://dx.doi.org/10.1016/S0924-2716(98)00009-4

Kretschmer U., Kirchner N., Morhart C., Spiecker H. (2013). A new approach to assessing tree stem quality characteristics using terrestrial laser scans. Silva Fennica 47: 1–14. http://dx.doi.org/10.14214/sf.1071

Kukko A. (2013). Mobile laser scanning – system development, performance and applications. Publications of the Finnish Geodetic Institute 153. 247p. http://urn.fi/URN:ISBN:978-951-711-307-6

Laasasenaho J. (1982). Taper curve and volume functions for pine, spruce and birch. Communicationes Institute Forestalis Fenniae 108. 74p.

Latifi H., Nothdurft A., Koch B. (2010). Non-parametric prediction and mapping of standing timber volume and biomass in a temperate forest: application of multiple optical/LiDAR-derived predictors. Forestry 83: 395–407. http://dx.doi.org/10.1093/forestry/cpq022

Lehtonen A., Mäkipää R., Heikkinen J., Sievänen R., Liski J. (2004). Biomass expansion factors (BEFs) for Scots pine, Norway spruce and birch according to stand age for boreal forests. Forest Ecology and Management 188: 211–224. http://dx.doi.org/10.1016/j.foreco.2003.07.008

Liang X. (2013). Feasibility of Terrestrial Laser Scanning for Plotwise Forest Inventories. Publications of the Finnish Geodetic Institute 149. 150p. http://urn.fi/URN:ISBN:978-951-711-299-4

Liang X., Hyyppä J. (2013). Automatic stem mapping by merging several terrestrial laser scans at the feature and decision levels. Sensors 13: 1614–1634. http://dx.doi.org/10.3390/s130201614

Liang X., Litkey P., Hyyppä J., Kaartinen H., Kukko A., Holopainen M. (2011). Automatic plot-wise tree location mapping using single-scan terrestrial laser scanning. Photogrammetric Journal of Finland 22: 37–48.

Liang X., Litkey P., Hyyppa J., Kaartinen H., Vastaranta M., Holopainen M. (2012). Automatic Stem Mapping Using Single-Scan Terrestrial Laser Scanning. IEEE Transactions on Geoscience and Remote Sensing 50: 661–670. http://dx.doi.org/10.1109/TGRS.2011.2161613

Lindberg E. (2012). Estimation of canopy structure and individual trees from laser scanning data. Acta Universitatis agriculturae Sueciae 33. 78p. http://pub.epsilon.slu.se/8888/

Lindberg E., Holmgren J., Olofsson K., Olsson H. (2012). Estimation of stem attributes using a combination of terrestrial and airborne laser scanning. European Journal of Forest Research 131: 1917–1931. http://dx.doi.org/10.1007/s10342-012-0642-5

Lu D. (2006). The potential and challenge of remote sensing-based biomass estimation. International Journal of Remote Sensing 27: 1297–1328. http://dx.doi.org/10.1080/01431160500486732

Maas H.-G., Bienert A., Scheller S., Keane E. (2008). Automatic forest inventory parameter determination from terrestrial laser scanner data. International Journal of Remote Sensing 29: 1579–1593. http://dx.doi.org/10.1080/01431160701736406

Malinen J., Berg V., Kilpeläinen H. (2010). Roundwood pricing mechanisms and their performance in Scots pine roundwood markets. Working Papers of the Finnish Forest Research Institute 174. http://www.metla.fi/julkaisut/workingpapers/2010/mwp174-en.htm

Maltamo M., Gobakken T. (2014). Predicting tree diameter distribution. In: Maltamo, M., Næsset, E., Vauhkonen, J. (Eds.). Forestry Applications of Airborne Laser Scanning – Concepts and Case Studies. Managing Forest Ecosystems 27. Springer. p. 177–191. http://dx.doi.org/10.1007/978-94-017-8663-8_9

Maltamo M., Mustonen K., Hyyppä J., Pitkänen J., Yu X. (2004). The accuracy of estimating individual tree variables with airborne laser scanning in a boreal nature reserve. Canadian Journal of Forest Research 34: 1791–1801. http://dx.doi.org/10.1139/x04-055

Maltamo M., Peuhkurinen J., Malinen J., Vauhkonen J., Tokola T. (2009). Predicting Tree Attributes and Quality Characteristics of Scots Pine Using Airborne Laser Scanning Data. Silva Fennica 43: 507–521. http://dx.doi.org/10.14214/sf.203

Moskal L.M., Zheng G. (2012). Retrieving Forest Inventory Variables with Terrestrial Laser Scanning (TLS) in Urban Heterogeneous Forest. Remote Sensing 4: 1–20. http://dx.doi.org/10.3390/rs4010001

Næsset E. (2002). Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. Remote Sensing of Environment 80: 88–99. http://dx.doi.org/10.1016/S0034-4257(01)00290-5

Næsset E. (2004). Estimation of above- and below-ground biomass in boreal forest ecosystems. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 36 (8/W2): 145–148.

Næsset E. (2009). Effects of different sensors, flying altitudes, and pulse repetition frequencies on forest canopy metrics and biophysical stand properties derived from small-footprint airborne laser data. Remote Sensing of Environment 113: 148–159. http://dx.doi.org/10.1016/j.rse.2008.09.001

Næsset E., Gobakken T. (2005). Estimating forest growth using canopy metrics derived from airborne laser scanner data. Remote Sensing of Environment 96: 453–465. http://dx.doi.org/10.1016/j.rse.2005.04.001

Packalén P., Maltamo M. (2008). Estimation of species-specific diameter distribution using airborne laser scanning and aerial photographs. Canadian Journal of Forest Research 38: 1750–1760. http://dx.doi.org/10.1139/X08-037

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

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

Pfeifer N., Winterhalder D. (2004). Modelling of tree cross sections from terrestrial laser scanning data with free-form curves. In International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 36 (8/W2): 76–81.

Popescu S.C. (2007). Estimating biomass of individual pine trees using airborne lidar. Biomass and Bioenergy 31: 646–655. http://dx.doi.org/10.1016/j.biombioe.2007.06.022

Popescu S.C., Wynne R.H., Nelson R.F. (2003). Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. Canadian Journal of Remote Sensing 29: 564–577. http://dx.doi.org/10.5589/m03-027

Popescu S.C., Wynne R.H., Scrivani J.A. (2004). Fusion of Small-Footprint Lidar and Multispectral Data to Estimate Plot- Level Volume and Biomass in Deciduous. Forest Science 50: 551–565.

Puttonen E., Jaakkola A., Litkey P., Hyyppä J. (2011). Tree classification with fused mobile laser scanning and hyperspectral data. Sensors 11: 5158–82. http://dx.doi.org/10.3390/s110505158

Puttonen E., Litkey P., Liang X., Kaartinen H., Kukko A. (2010a). Single tree canopy projection area extraction from single-scan terrestrial laser scanner data. In proceedings of Silvilaser 2010. Freiburg, Germany. 54–64.

Puttonen E., Suomalainen J., Hakala T., Räikkönen E., Kaartinen H., Kaasalainen S., Litkey P. (2010b). Tree species classification from fused active hyperspectral reflectance and LiDAR measurements. Forest Ecology and Management 260: 1843–1852. http://dx.doi.org/10.1016/j.foreco.2010.08.031

Räty M., Kankare V., Yu X., Holopainen M., Vastaranta M., Kantola T., Hyyppä J., Viitala R. (2011). Tree biomass estimation using ALS features. In proceedings of Silvilaser 2011. Hobart, Australia. 16–20.

Raumonen P., Kaasalainen M., Åkerblom M., Kaasalainen S., Kaartinen H., Vastaranta M., Holopainen M., Disney M., Lewis P. (2013). Fast Automatic Precision Tree Models from Terrestrial Laser Scanner Data. Remote Sensing 5: 491–520.

http://dx.doi.org/10.3390/rs5020491

Repola J. (2008). Biomass Equations for Birch in Finland. Silva Fennica 42: 605–624.
http://dx.doi.org/10.14214/sf.236

Repola J. (2009). Biomass Equations for Scots Pine and Norway Spruce. Silva Fennica 43: 625–647.
http://dx.doi.org/10.14214/sf.184

Rönnholm P., Hyyppä J., Hyyppä H., Haggrén H., Yu X., Kaartinen H. (2004). Calibration of laser-derived tree height estimates by means of photogrammetric techniques. Scandinavian Journal of Forest Research 19: 524–528.
http://dx.doi.org/10.1080/02827580410019436

Saarinen N., Vastaranta M., Kankare V., Tanhuanpää T., Holopainen M., Hyyppä J., Hyyppä H. (2014). Urban-Tree-Attribute Update Using Multisource Single-Tree Inventory. Forests 5: 1032–1052.
http://dx.doi.org/10.3390/f5051032

Sithole G., Vosselman G. (2004). Experimental comparison of filter algorithms for bare-Earth extraction from airborne laser scanning point clouds. ISPRS Journal of Photogrammetry and Remote Sensing 59: 85–101.
http://dx.doi.org/10.1016/j.isprsjprs.2004.05.004

Srinivasan S., Popescu S.C., Eriksson M., Sheridan R.D., Ku N.-W. (2014). Multi-temporal terrestrial laser scanning for modeling tree biomass change. Forest Ecology and Management 318: 304–317.
http://dx.doi.org/10.1016/j.foreco.2014.01.038

StanFord (2009). Standard for forestry data and communication. SkogForsk.
http://www.skogforsk.se/ [Cited 25. February 2014]

Stängle S.M., Brüchert F., Kretschmer U., Spiecker H., Sauter U.H. (2014). Clear wood content in standing trees predicted from branch scar measurements with terrestrial LiDAR and verified with x-ray computed tomography. Canadian Journal of Forest Research 44: 145–153.
http://dx.doi.org/10.1139/cjfr-2013-0170

Thies M., Pfeifer N., Winterhalder D., Gorte B.G.H. (2004). Three-dimensional reconstruction of stems for assessment of taper, sweep and lean based on laser scanning of standing trees. Scandinavian Journal of Forest Research 19: 571–581.
http://dx.doi.org/10.1080/02827580410019562

TopoSys (1996). Digital Elevation Models, Services and Products. Toposys GMbH, Germany.

Ullrich A., Studnicka N., Hollaus M., Briese C., Wolfgang W., Doneus M., Mücke W. (2007). Improvements in DTM generation by using full-waveform airborne laser scanning data. In 7th International Conference on '''Laser Scanning and Digital Aerial Photography. Today and Tomorrow." Moscow, Russia.

Uusitalo J. (1997). Pre-harvest measurement of pine stands for sawing production planning. Acta Forestalia Fennica 259, 1–56.
http://hdl.handle.net/10138/27297

Uusitalo J., Isotalo J. (2005). Predicting knottiness of Pinus sylvestris for use in tree bucking procedures. Scandinavian Journal of Forest Research 20: 521–533.
http://dx.doi.org/10.1080/02827580500407109

Vastaranta M., Holopainen M., Yu X., Hyyppä J., Mäkinen A., Rasinmäki J., Melkas T., Kaartinen H., Hyyppä H. (2011). Effects of Individual Tree Detection Error Sources on Forest Management Planning Calculations. Remote Sensing 3: 1614–1626. http://dx.doi.org/10.3390/rs3081614

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

Vastaranta M., Saarinen N., Kankare V., Holopainen M., Kaartinen H., Hyyppä J., Hyyppä H. (2014). Multisource Single-Tree Inventory in the Prediction of Tree Quality Variables and Logging Recoveries. Remote Sensing 6: 3475–3491. http://dx.doi.org/10.3390/rs6043475

Vauhkonen J., Ene L., Gupta S., Heinzel J., Holmgren J., Pitkanen J., Solberg S., Wang Y., Weinacker H., Hauglin K.M., Lien V., Packalen P., Gobakken T., Koch B., Naesset E., Tokola T., Maltamo M. (2012). Comparative testing of single-tree detection algorithms under different types of forest. Forestry 85: 27–40. http://dx.doi.org/10.1093/forestry/cpr051

Vauhkonen J., Korpela I., Maltamo M., 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. http://dx.doi.org/10.1016/j.rse.2010.01.016

Vauhkonen J., Ørka H.O., Holmgren J., Dalponte M., Heinzel J., Koch B. (2014). Tree species recognition based on airborne laser scanning and complementary data sources. In Maltamo, M., Næsset, E., Vauhkonen, J. (Eds.). Forestry Application of Airborne Laser Scanning: Concepts and Case Studies, Managing Forest Ecosystems 27. Springer. p. 135–156. http://dx.doi.org/10.1007/978-94-017-8663-8_7

Vauhkonen J., Packalen P., Malinen J., Pitkänen J., Maltamo M. (2013). Airborne laser scanning-based decision support for wood procurement planning. Scandinavian Journal of Forest Research 29: 132–143. http://dx.doi.org/10.1080/02827581.2013.813063

Vauhkonen J., Tokola T., Packalén P., Maltamo M. (2009). Identification of Scandinavian Commercial Species of Individual Trees from Airborne Laser Scanning Data Using Alpha Shape Metrics. Forest Science 55: 37–47.

White J.C., Wulder M.A., Varhola A., Vastaranta M., Coops N.C., Cook B.D., Pitt D., Woods M. (2013). A best practices guide for generating forest inventory attributes from airborne laser scanning data using an area-based approach. The Forestry Chronicle 89: 722–723. http://dx.doi.org/10.5558/tfc2013-132

Yu X., Hyyppä J., Vastaranta M., Holopainen M., Viitala R. (2011). Predicting individual tree attributes from airborne laser point clouds based on the random forests technique. ISPRS Journal of Photogrammetry of Remote Sensing 66: 28–37. http://dx.doi.org/10.1016/j.isprsjprs.2010.08.003

Yu X., Liang X., Hyyppä J., Kankare V., Vastaranta M., Holopainen M. (2013). Stem biomass estimation based on stem reconstruction from terrestrial laser scanning point clouds. Remote Sensing Letters 4: 344–353.

http://dx.doi.org/10.1080/2150704X.2012.734931

Zhao K., Popescu S., Nelson R. (2009). Lidar remote sensing of forest biomass: A scale-invariant estimation approach using airborne lasers. Remote Sensing of Environment 113: 182–196.
http://dx.doi.org/10.1016/j.rse.2008.09.009