Estimation of Canopy Structure and Individual Trees from Laser Scanning Data

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Cover: Side view of a 4 m wide transect of airborne laser scanning (ALS) data from a mixed forest (with birch and coniferous trees). The ALS data have been clustered (Paper II) to separate returns from the dominant tree layer (black) and returns from the shrubs below (red; cluster mean height ≤ 7.5 m).

(image: E. Lindberg)

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Abstract

During the last fifteen years, laser scanning has emerged as a data source for forest inventory. Airborne laser scanning (ALS) provides 3D data, which may be used in an automated analysis chain to estimate vegetation properties for large areas. Terrestrial laser scanning (TLS) data are highly accurate 3D ground-based measurements, which may be used for detailed 3D modeling of vegetation elements.

The objective of this thesis is to further develop methods to estimate forest information from laser scanning data. The aims are to estimate lists of individual trees from ALS data with accuracy comparable to area-based methods, to collect detailed field reference data using TLS, and to estimate canopy structure from ALS data. The studies were carried out in boreal and hemi-boreal forests in Sweden.

Tree crowns were delineated in three dimensions with a model-based clustering approach. The model-based clustering identified more trees than delineation of a surface model, especially for small trees below the dominant tree layer. However, it also resulted in more erroneously delineated tree crowns. Individual trees were estimated with statistical methods from ALS data based on field-measured trees to obtain unbiased results at area level. The accuracy of the estimates was similar for delineation of a surface model (stem density root mean square error or RMSE 32.0%, bias 1.9%; stem volume RMSE 29.7%, bias 3.8%) as for model-based clustering (stem density RMSE 33.3%, bias 1.1%; stem volume RMSE 22.0%, bias 2.5%).

Tree positions and stem diameters were estimated from TLS data with an automated method. Stem attributes were then estimated from ALS data trained with trees found from TLS data. The accuracy (diameter at breast height or DBH RMSE 15.4%; stem volume RMSE 34.0%) was almost the same as when trees from a manual field inventory were used as training data (DBH RMSE 15.1%; stem volume RMSE 34.5%).

Canopy structure was estimated from discrete return and waveform ALS data. New models were developed based on the Beer-Lambert law to relate canopy volume to the fraction of laser light reaching the ground. Waveform ALS data (canopy volume RMSE 27.6%) described canopy structure better than discrete return ALS data (canopy volume RMSE 36.5%). The methods may be used to estimate canopy structure for large areas.

Keywords: forest inventory, individual trees, canopy structure, laser scanning, LiDAR, ALS, TLS

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Contents

List of Publications

This thesis is based on the work contained in the following papers, referred to by Roman numerals in the text:

I Lindberg, E., Holmgren, J., Olofsson, K., Wallerman, J., & Olsson, H. (2010). Estimation of tree lists from airborne laser scanning by combining single-tree and area-based methods. *International Journal of Remote Sensing* 31(5), 1175-1192.

II Lindberg, E., Holmgren, J., Olofsson, K., Wallerman, J., & Olsson, H. Estimation of tree lists from airborne laser scanning using model-based clustering and k-MSN imputation (manuscript).

III Lindberg, E., Holmgren, J., Olofsson, K., & Olsson, H. Estimation of stem attributes using a combination of terrestrial and airborne laser scanning. *European Journal of Forest Research* Accepted

IV Lindberg, E., Olofsson, K., Holmgren, J., & Olsson, H. (2012). Estimation of 3D vegetation structure from waveform and discrete return airborne laser scanning data. *Remote Sensing of Environment* 118, 151-161.

Papers I and IV are reproduced with the permission of the publishers.

The contribution of Eva Lindberg to the papers included in this thesis was as follows:

I Developed the statistical approaches to estimate lists of individual trees, performed the analyses, and wrote the major part of the manuscript.

II Developed the model-based clustering approach, performed the analyses, and wrote the major part of the manuscript.

III Developed the second part of the method to estimate diameters, performed the analyses, and wrote the major part of the manuscript.

IV Planned and managed the field inventory, developed the method to normalize the waveforms, developed the methods to estimate vegetation volume from airborne laser scanning data, performed the analyses, and wrote the major part of the manuscript.

Abbreviations

3D	Three-Dimensional
ALS	Airborne Laser Scanning
CHP	Canopy Height Profile
CS	Correlation Surface
DBH	Diameter at Breast Height
DEM	Digital Elevation Model
EM	Expectation–Maximization
FRI_C	First Return Intensity in Canopy stratum
FRI_G	First Return Intensity in Ground stratum
GER	Generalized Ellipsoid of Revolution
GPS	Global Positioning System
IMU	Inertial Measurement Unit
ITC	Individual Tree Crown
k-MSN	k Most Similar Neighbours
k-NN	k Nearest Neighbours
LAD	Leaf Area Density
LAI	Leaf Area Index
LiDAR	Light Detection And Ranging
nDSM	normalized Digital Surface Model
NFI	National Forest Inventory
RMSE	Root Mean Square Error
RTM	Radiative Transfer Model
TIN	Triangular Irregular Network
TLS	Terrestrial Laser Scanning

1 Introduction

Forest resources are important because of their economic value as well as their ecological values and different ecosystem services. Inventories of forest resources are conducted on a variety of scales. National forest inventories (NFI) and national inventories of landscapes provide information about the forest state at national and regional level to authorities and researchers, Environment protection agencies and regional authorities need forest information to identify areas of high ecological value. Forest owners need stand maps with associated forest variables such as stem volume and habitat type for forest management planning but also more detailed information, especially in forest stands that are candidates for forest management actions. Forest inventory requires consideration of the desired accuracy and the available resources (i.e., technical and financial).

During the last century, statistical sampling approaches based on field measurements (e.g., trees measured in sample plots or relascope point measurements) have been used to collect information regarding the state of forest resources for large areas (e.g., Jonsson *et al.*, 1993), in particular national forest inventories (Axelsson *et al.*, 2010). For the purpose of stand-wise forest management planning, inventories are often done by more subjective measurements of forest stands (Ståhl, 1992). After the introduction of aerial images, manual photo interpretation has been used to delineate forest stands and determine forest variables such as tree species, tree height, and stem volume (Axelson, 1993). Three-dimensional (3D) interpretation of aerial images was introduced early in the history of aerial images by using stereo photogrammetric methods, which may be used to determine tree species and stem volume for forest management planning (Åge, 1985).

Manual photo interpretation is one remote sensing technique, where remote sensing refers to a technology to obtain information about properties of the earth and different objects from a distance. Interpretation of satellite imagery is another remote sensing technique, which may be combined with field measurements of sample plots to automatically produce wall-to-wall estimates of forest variables (Nilsson, 1997) or habitat maps (McDermid, 2006). Data from radar sensors carried by satellites or aircrafts can also be used to derive information useful for forest inventory (e.g., Magnusson, 2006; Sandberg *et al.*, 2011). With the development of new sensors and positioning devices, laser scanning technologies have become available, providing highly accurate 3D coordinate measurements of vegetation and ground. The rapid development of electronics during the last decades has made these technologies affordable and widely available. This presents efficient ways of obtaining information for large areas (McRoberts *et al.*, 2010). Further development of automated methods to analyze the data is essential to utilize the vast amount of data produced by the sensors.

1.1 Laser scanning

1.1.1 Distance measurements

Data from laser scanning are 3D coordinate measurements of light reflections from the ground and other objects. Laser scanning is based on Light Detection And Ranging (LiDAR). The laser scanner emits laser light and measures the light reflected back from different objects. The distance to the objects can be determined with one of two different principles: Time-of-flight or continuous wave (Petrie & Toth, 2009b). With the time-of-flight principle, the laser scanner emits a short pulse of light and measures the time it takes for the light to be reflected back. The distance may be determined since the speed of light is known. With the continuous wave principle, the laser scanner emits continuous, phase modulated light and measures the phase of the reflected light. The distance may be determined since the phase of the light acts as a fingerprint unique for the time when it was emitted. Continuous wave measurements are usually more accurate than time-of-flight measurements. However, the maximum range of continuous wave measurements is the length of the modulated wavelength, which is typically around 100 m (Petrie & Toth, 2009b).

1.1.2 Discrete return and waveform laser data

Most commercial laser scanning systems deliver discrete returns, also known as point laser data. The discrete returns represent high intensity peaks in the reflected light corresponding to surfaces from which the light has been reflected (figure 1). The discrete returns are derived during the data acquisition from the received signal. Common criteria for detection of a discrete return are when the intensity value reaches a maximum (i.e., peak detection), when the intensity value exceeds a defined threshold (i.e., leading edge detection) or when the intensity value of a peak exceeds a fraction of the peak maximum (i.e., constant fraction detection) in which case the received signal must be saved temporarily (Stilla & Jutzi, 2009). Due to limitations in the electronics of most laser scanning systems, only sufficiently spaced peaks are distinguished as separate returns. However, with the development of sensors and electronics, waveform laser data have also become available from commercial laser scanning systems. Waveform laser data are intensity values of the reflected laser light measured at short, regular intervals (Stilla & Jutzi, 2009). Waveform laser data describe the whole backscattered signal and allow for more detailed processing, for example, derivation of returns from the waveforms using more advanced algorithms (Persson *et al.*, 2005).

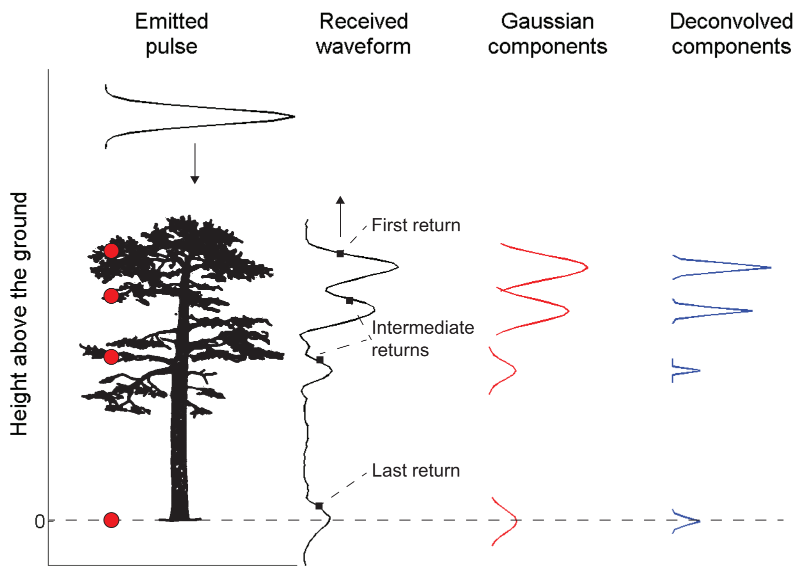

Figure 1. The emitted pulse is reflected from different surfaces, resulting in a waveform that can be used to derive discrete returns. The waveform may also be decomposed into Gaussian components and deconvolved to obtain more detailed information about the reflecting surfaces.

The intensity value is a measure of the energy flux (i.e., the received power per area unit). Assuming a diffuse reflecting surface equal to or larger than the laser footprint, the received optical power P_r is described by equation 1 (Wehr, 2009)

$$P_r = P_T \times \tau_{total} \times \frac{1}{w} \times \frac{D^2}{R^4} \times \sigma_{cross} \quad (1)$$

where P_T is the transmitted power, τ_{total} is the total transmission (i.e., the transmission of the receiver objective, the optical interference filter, and the scanning device as well as the two-way transmission of the atmosphere), ω is the divergence of the laser beam, D is the diameter of the receiving aperture, R is the distance from the laser scanning system to the reflecting surface, and σ_{cross} is the cross-section of the reflecting surface. The cross-section σ_{cross} is proportional to the product of the reflectance ρ and the illuminated area A_s of the reflecting surface (Danson *et al.*, 2009). The surface roughness may also be included as a term Ω in the denominator of the cross-section to describe the spreading of the reflected light from the surface (Equation 2; Wagner *et al.*, 2006).

$$\sigma_{cross} = \tfrac{4\pi}{\Omega}\rho A_s \tag{2}$$

Assuming that the influence of the receiver and amplifier as well as the atmosphere is constant, the received waveform depends mainly on the emitted pulse and the reflecting surface. Since the emitted pulse is not infinitely short, the received waveform will be the convolution between the emitted pulse and the surface properties (Stilla & Jutzi, 2009). Deconvolution of the waveform is necessary to distinguish surfaces separated by a smaller distance than the order of the length of the emitted pulse. The duration of the emitted pulse is typically 4-10 ns, which means that the length of the pulse is around 1.2-3 m.

A common model is to assume that a cluster of scatterers may be described by a Gaussian function (Equation 3)

$$\sigma_i(t) = \hat{\sigma}_i e^{\frac{(t-t_i)^2}{2s_i^2}} \tag{3}$$

where t_i specifies the position of cluster i, $\hat{\sigma}_i$ is the amplitude of the cluster, and s_i is the standard deviation or the width of the cluster. Since the emitted pulse may also be approximated with a Gaussian function (Wagner *et al.*, 2006), the resulting convoluted signal is another Gaussian function, which has appealing properties for deconvolution (Roncat *et al.*, 2011). After deconvolution, the position, amplitude, and standard deviation may be derived for each echo by modelling the waveform as a series of Gaussian components. If reference data for calibration of the laser scanning system are available, it is possible to derive the backscatter cross-section for each component (Wagner *et al.*, 2006). Gaussian models are computationally heavy and assume symmetry of the emitted pulse as well as the scatterers. Therefore, B-splines have been suggested for the modelling of waveforms (Roncat *et al.*, 2011).

For a given laser scanning system and assuming that the transmission is constant, the intensity value of the reflected light depends on the power of the emitted pulse, the size and reflectance of the reflecting surface, and the distance from the scanner to the reflecting surface (Danson *et al.*, 2009). Additionally, the gain of the sensor might be adjusted depending on the conditions at the moment when the light is received. To estimate the reflectance properties of the reflecting surface in physical units, information about the power of the emitted pulse, the sensor gain, and the distance to the reflecting surface is necessary.

1.1.3 Airborne laser scanning

Airborne laser scanning (ALS) is usually based on the time-of-flight principle (Petrie & Toth, 2009b). To determine the coordinates of the laser reflections, the position and orientation of the laser scanning system is measured with a global positioning system (GPS) and an inertial measurement unit (IMU) to keep track of the direction of each emitted pulse as well as the position of the laser scanning system at every moment (El-Sheimy, 2009). The GPS and IMU are complementary. The GPS provides position and velocity while the IMU provides orientation information based on accelerometers. The IMU can also detect and correct missing or erroneous GPS measurements. The IMU residual errors are calibrated using the GPS measurements (El-Sheimy, 2009). ALS data are geo-referenced from the distances measured by the laser scanning system and the position and orientation information provided by the GPS and IMU.

The general spatial distribution of the ALS measurements on the ground is determined by the scanning mechanism of the laser scanner, the scan angle, the flying altitude and speed, and the pulse repetition frequency (Petrie & Toth, 2009a). The scan angle is the maximum angle of the laser beam from the vertical direction. A larger scan angle or a higher flying altitude or speed will result in a smaller measurement density (i.e., density of measured points on the ground) but a higher spatial coverage. A higher pulse repetition frequency will result in a higher measurement density. The beam divergence is the angle at which the light of the laser beam spreads. The beam divergence and the flying altitude determine the footprint, which is the area covered by the laser beam on the ground.

The accuracy of the measurements on hard surfaces is typically around ±0.5 m in the horizontal direction and ±0.2 m in the vertical direction from a flying altitude of around 1000 m (Habib, 2009). The development of ALS technology has increased the pulse repetition frequency, making high spatial coverage possible without decreased measurement density. The pulse repetition frequency of the first experimental profiling pulsed laser systems was approximately 100-400 Hz (Nelson *et al.*, 1988a; Nelson *et al.*, 1988b). At the time when laser scanning became commercially available, the pulse repetition frequency had increased around ten times, resulting in a measurement density of around 0.1 m^{-2} from a flying altitude of 640-825 m (Næsset, 1997). A few years later, laser scanning systems with a pulse repetition frequency of 83 kHz had been developed, resulting in a measurement density of around 10 m^{-2} from a flying altitude of 400 m (Hyyppä & Inkinen, 1999). Current laser scanning systems typically use a pulse repetition frequency of around 150 kHz, resulting in a measurement density of around 10 m^{-2} with a larger scan angle to enable higher spatial coverage (Vastaranta *et al.*, 2012). Modern ALS systems can emit a new pulse without waiting for the reflection from the previous pulse, so-called multiple pulses, which enables higher pulse repetition frequencies for higher flying altitude (Petrie & Toth, 2009b). State-of-the art ALS systems have pulse repetition frequencies up to 500 kHz (*ALTM PEGASUS HD500 Summary Specification Sheet*, 2012).

1.1.4 Terrestrial laser scanning

Terrestrial laser scanning (TLS) provides highly accurate 3D coordinate measurements of light reflections from the surfaces surrounding the scanner. TLS systems using continuous wave distance measurements as well as TLS systems using time-of-flight distance measurements are common. TLS systems have also been developed for collecting waveform laser data (Jupp *et al.*, 2005). TLS systems may also be classified by their coverage (Staiger, 2003; Petrie & Toth, 2009c): *i*. Panoramic-type TLS systems rotate around a vertical axis to provide a full 360° horizontal coverage and typically a minimum 180° vertical coverage (i.e., a hemispheric coverage). *ii*. Hybrid TLS systems also provide a 360° horizontal coverage but the vertical coverage is restricted to 50°-60°. *iii*. Camera-type scanners have a limited field of view similar to an ordinary camera, typically 40° × 40°. New sensors such as distance cameras will make the equipment needed for the data collection more portable and the cost will most likely be lower. TLS data are geo-referenced from the distances measured by the laser scanning system, the angles of the laser beam in the horizontal and vertical plane, and the position of the laser scanner, usually measured with a high precision GPS.

1.1.5 Processing chain

The processing of laser scanning data typically consists of steps similar to those used in digital image processing (Gonzalez & Woods, 2008): Data acquisition, pre-processing, segmentation, representation with feature extraction from the segments, and classification (Holmgren, 2003). The acquisition of laser data is described in the preceding sections. The pre-processing of laser scanning data includes geo-referencing of the laser measurements as well as strip adjustment and quality assurance. Pre-processing of waveform laser data may also include derivation of returns. For the purpose of forest inventory, the pre-processing step includes classification of the returns into ground returns and possibly other classes such as vegetation or buildings, exclusion of erroneous laser measurements, and derivation of a digital elevation model (DEM) from the ground returns.

The purpose of the segmentation step is to assign data to different groups based on coordinates or other properties such as the intensity values of the laser returns. The segmentation may be done directly from the laser data or from pixels (i.e., surface models) or voxels (i.e., volume elements, representing values on a regular grid in three dimensional space; analogous to pixels in three dimensions) derived from the laser data. Detailed models of objects can be derived from the point clouds with 3D modelling (Pfeifer & Briese, 2007; Rönnholm *et al.*, 2007). The features may be extracted from the shapes of the objects or from the distribution of laser returns within the objects. The classification step may be realised with a classification scheme to assign the objects into different groups or with other statistical models or pattern recognition methods to estimate information of interest. The classification may be based on reference data or training data (i.e., measurements or observations of the information of interest for a subsample of objects covered by the laser scanning data) or on previously established models of the relationship between the information of interest and extractable features. A statistical approach may also be used to control the parameters of the earlier steps in the processing chain, for example, the parameters of the segmentation or the selection of features.

1.1.6 Use of laser scanning for forest inventory

Since ALS measures both the height of vegetation elements and the ground, it is possible to derive information about the vegetation from the data. Derivation of information about vegetation from remotely sensed data is usually done by establishing models based on the relationship between the remotely sensed data and reference data, also known as training data, for the information of interest. In the case of vegetation, the reference data are field observations or measurements. The established models can be applied to the whole area covered by the remotely sensed data to estimate the information of interest. ALS data provide unique possibilities for automated analysis of the ground height and properties of the vegetation for large areas.

A second possibility provided by laser scanning data is to derive information that is unrealistic to measure manually. ALS data are measurements of the ground, the vegetation, and other objects. The vegetation measurements are reflections from foliage and branches, and the spatial distribution of the measurements are related to the distribution of the canopy of the trees and shrubs. TLS data can also be used to measure vegetation. The measurements may be used to derive information about the stem forms for forest management planning or about the canopy structure for ecological applications. Such detailed information is difficult and expensive to measure manually.

During the last fifteen years, ALS data have been used for estimation of forest variables such as tree height and stem volume (Nilsson, 1996; Næsset, 1997; Hyyppä & Inkinen, 1999). Two main approaches are used for estimation of forest variables from ALS data (Hyyppä *et al.*, 2008): *i*. Area-based methods when mean and total values of forest variables per area unit measured in field plots are used as training data for statistical models or pattern recognition methods to estimate the same variables from features extracted from the ALS data in raster cells. *ii*. Individual tree methods when tree crowns are delineated from the ALS data and sometimes linked to field-measured trees to train models for estimation of stem attributes. Area-based approaches are based on the strong correlation between forest variables and features extracted from the ALS data and require only low density ALS data. On the other hand, they require larger training datasets than individual tree methods. Individual tree methods enable high precision forestry and provide more information about the forest. On the other hand, they require denser ALS data and more complex algorithms (Hyyppä *et al.*, 2008). Linking of tree crowns delineated from ALS data to field-measured trees requires positions of the field-measured trees, which has been a limitation due to the additional manual field work. The approaches may also be combined in different ways to utilize their respective advantages.

1.2 Area-based methods for airborne laser scanning

An area-based method in the context of airborne laser scanning for forest inventory is an approach to estimate summary values of forest variables in area units, for example, mean tree height or stem volume per hectare, from variables derived from ALS data in area units, typically with a size of 100-500 m^2. The estimation is done by deriving and selecting variables from the ALS data that are correlated with forest variables measured in geo-referenced field plots and creating models with the field-measured values as dependent variables and the ALS variables as independent variables (Næsset & Bjerknes, 2001).

Due to differences between the laser scanning systems and the due to the vegetation properties (e.g., phenology) during the acquisition of the ALS data, the coefficients of the models are unique for each acquisition. When the models have been established, the models can be used to estimate the same forest variables for the whole area covered by ALS data from the same acquisition and the estimates can be aggregated to stand level (Næsset, 2002). Using separate models for different strata may increase the accuracy of the estimation (Næsset *et al.*, 2004). Stratification of the area is often done by photo interpretation of the tree species composition in forest stands.

The most common variables derived from the ALS data are measures of the distribution of the height above the ground of ALS returns (i.e., percentiles) and density measures of the vegetation such as the fraction of ALS returns above a certain threshold, for example, 2 m above the ground (Næsset *et al.*, 2004), where the ground level is represented by a DEM derived from the ALS data. Other approaches have also been used. For example, stem volume or biomass can be estimated with a regression model from canopy volume defined as the entire volume between the top of the canopy and the ground surface. The canopy volume is calculated for different canopy height intervals as the mean height of first returns multiplied by the fraction of first returns occurring in the specified height interval (Hollaus *et al.*, 2009c). The variables may also include measures of the horizontal structure of the ALS data (Pippuri *et al.*, 2011) or information about individual tree crowns that may be derived from the ALS data and aggregated over each field plot or raster cell (Holmgren & Wallerman, 2006).

The estimation may be done with multiple regression models or with non-parametric methods. Non-parametric methods are estimation techniques with little *a priori* knowledge about the relationship between the dependent and independent variables (Altman, 1992), for example, k nearest neighbours (k-NN; Hudak *et al.*, 2008) or random forest (Breidenbach *et al.*, 2010b). Non-parametric methods generally require larger training datasets since the estimation is based on having "sufficiently" similar observations while a regression model will interpolate or extrapolate well for even a few observations, provided a strong linear relationship (Moeur & Stage, 1995). An additional estimation method is k most similar neighbours (k-MSN; Packalén & Maltamo, 2007), where the similarity between observations is based on canonical correlations and Mahalanobis distance. One advantage of k-NN and k-MSN methods is that the covariance structure between the different forest variables is reasonably maintained if k is equal to one since the estimation is based on imputation of observations.

k-MSN has been applied to a combination of ALS data and aerial images to estimate tree species specific stand variables with promising results (Packalén & Maltamo, 2007). An advantage of k-MSN is that the estimates are consistent in the sense that, for example, the total stem volume per area unit is exactly the sum of the stem volume of the different tree species. Forest variables related to vegetation height and density may be estimated from ALS data with high accuracy but estimation of tree species composition is more accurate when including optical data such as aerial images (Bork & Su, 2007) or satellite imagery (Nordkvist *et al.*, 2012). ALS data have also been combined with features extracted from aerial images and *a priori* information (i.e., site condition, main tree species, and stand development) from a stand register to estimate forest variables (Maltamo *et al.*, 2006b).

Area-based methods produce estimates of mean tree height, mean diameter at breast height (DBH), basal area, and stem volume with errors of the same size as from accurate sampling-based field inventories (i.e., using several field plots within each forest stand; Holmgren, 2004; Maltamo *et al.*, 2006a; Næsset, 2007; Säynäjoki *et al.*, 2008; Breidenbach *et al.*, 2010b). Stand delineation and estimation of stand variables are possible for large areas using automated and computationally efficient methods (Hollaus *et al.*, 2009a; Koch *et al.*, 2009). Area-based methods are cost-efficient since lower measurement density of the ALS data than that needed for individual tree methods is sufficient, with typically around one emitted pulse per square metre (Säynäjoki *et al.*, 2008). However, most of the currently used area-based methods only consider the vertical distribution of the ALS data, which does not make use of the 3D structure of the ALS data. Additionally, estimation of forest variables in raster cells makes it difficult to derive information about tree species or lists of tree stems.

1.2.1 Diameter distributions

The distributions of tree height, DBH, and basal area in forest stands are often described with Weibull functions where the parameters may be estimated from stand variables measured in field such as total basal area and stem volume (e.g., Maltamo, 1997). The parameters of the Weibull function are simple to estimate and Weibull functions may be fitted to various distributions (Bailey & Dell, 1973). The parameters of Weibull functions may be estimated from forest variables estimated from ALS data (Maltamo *et al.*, 2004). The parameters have also been estimated directly from ALS data for DBH and basal area distributions (Gobakken & Næsset, 2004; Breidenbach *et al.*, 2008). Non-parametric distributions of tree height, DBH, and basal area may also be described using percentiles. Percentiles of DBH distributions have been estimated from ALS data using area-based methods with partial least squares regression and seemingly unrelated regression (Gobakken & Næsset, 2005; Bollandsås & Næsset, 2007). DBH distributions have also been estimated from ALS data with k-MSN imputation of field plots (Packalén & Maltamo, 2008; Maltamo *et al.*, 2009). The result from individual tree methods may be combined with measures of ALS data at plot level to estimate the distribution of tree height and DBH (Holmgren & Wallerman, 2006). To make the stem number, total basal area, and stem volume at area level consistent, the distributions may be adjusted using calibration estimation (Maltamo *et al.*, 2007). The tree size distributions are abstractions of the state of the forest stands. Parametric distributions are based on assumptions of the distributions of tree sizes and may not fully describe multi-layered forest stands. Non-parametric distributions (e.g., percentiles) are more flexible but rely on models created from the training data, which means that they generally require larger training datasets.

1.2.2 Canopy structure

The canopy structure can be defined as the spatial distribution of vegetation material (i.e., tree stems, foliage, and branches) of the trees and shrubs in an area. Canopy structure is related to the distribution of tree heights and DBH as well as the tree species composition. The vertical vegetation structure is the distribution of vegetation material as a function of height above ground. This is of interest for vegetation succession (Falkowski *et al.*, 2009) and fire behaviour modelling (Hall *et al.*, 2005) as well as for habitat studies (Brokaw & Lent, 1999), for example, habitat mapping of bird species (Lefsky *et al.*, 2002; Hill *et al.*, 2004; Clawges *et al.*, 2008). The horizontal vegetation structure is useful, for example, for identification of aforestation on less used pasture land and for mapping of the arctic or alpine tree line (Rees, 2007).

Large area monitoring of vegetation attributes relevant for nature conservation is today based on interpretation of optical remotely sensed data combined with field inventory (Vierling *et al.*, 2008). However, vertical vegetation structure is difficult to estimate from optical remotely sensed data. High density airborne laser scanning provides detailed information about the height distribution of vegetation elements (Shugart *et al.*, 2010). This information can be used for describing the vegetation structure and, to some degree, obtaining information about the height and density of different canopy layers, the shrub layer, and the field layer. This offers the potential to carry out detailed mapping that is not possible with currently operational remote sensing technique as well as efficient mapping for large areas. Canopy structure has this far mostly been estimated with area-based approaches from ALS data.

Canopy layers

Leaf area index (LAI) is the total one-sided leaf area per unit ground surface area (Wilson, 2011). LAI has been estimated from discrete return ALS data (Morsdorf *et al.*, 2006; Solberg *et al.*, 2009; Korhonen *et al.*, 2011). Leaf area density (LAD) is the total one-sided leaf area per unit of layer volume (Wilson, 2011). LAD can be interpreted as profiles of LAI, and the sum of the LAD over all layers is the LAI (Morsdorf *et al.*, 2006). The exact value of LAD is costly and laborious to measure since it requires destructive sampling of trees. LAD has been estimated from the decay rate of the returns derived from deconvolved waveform ALS data together with the fraction of ALS returns in different height intervals (Adams *et al.*, 2012). The decay rate was also found to be useful to differentiate returns from foliage from those from branches, stems, understory, and the ground.

Crown coverage of trees may be estimated with high accuracy from ALS data (Holmgren *et al.*, 2008a). Since part of the laser light will pass through gaps in a canopy (Harding, 2009), mapping of the understory is also possible to some degree (Hill & Broughton, 2009; Martinuzzi *et al.*, 2009). Single-layered and multi-layered stand structures may be separated using the shape of the distribution of discrete return ALS data (Maltamo *et al.*, 2005) or the height variability of local maxima in a canopy surface model derived from the ALS returns (Zimble *et al.*, 2003). The height of the herbaceous layer, understory shrub, and overstory tree layer has been estimated from the average height of all laser returns falling in each height interval (Su & Bork, 2007). Characterization of forest ecological variables is possible from the vegetation cover in different height intervals as described by the height distribution of ALS returns (Miura & Jones, 2010). By fitting, for example, a Weibull function to the height distribution of ALS returns, a quantitative measure of the vertical vegetation structure may be derived (Coops *et al.*, 2007). To describe multi-layered forest stands better, the use of mixture models has been proposed (Jaskierniak *et al.*, 2011). Waveform ALS data from the experimental SLICER system at NASA have been used to estimate a canopy height profile (CHP) that quantitatively represented the relative vertical distribution of canopy surface area and seemed to be correlated with a CHP measured in field, defined as a relative distribution of plant area as a function of height (Harding *et al.*, 2001). The analysis included a method to account for occlusion of the laser energy by canopy surfaces, transforming the backscatter signal to a CHP.

Even if several studies have modelled the vertical vegetation structure from ALS data, few of them have validated the results against detailed field measurements. Harding *et al.* (2001) estimated canopy height profiles for four selected forest stands from ALS data from SLICER using measurements from a telephoto lens calibrated to measure distances as reference data. Hilker *et al.* (2010) estimated canopy volume profiles for four forest stands from discrete return ALS data and compared them with canopy volume profiles estimated from terrestrial laser scanning. Hosoi *et al.* (2010) estimated LAD in a forest plot from discrete return ALS data and compared with LAD estimated from TLS data. Adams *et al.* (2012) estimated LAD from waveform ALS data and compared the results with LAD derived from destructive sampling in ten field plots. All four studies showed reasonably good agreement between the estimates from ALS data and field measurements.

Modelling approaches

The effects of canopy structure on the ALS waveform may be described by a 3D radiative transfer model (RTM; Ni-Meister *et al.*, 2001; Morsdorf *et al.*, 2009; Yang *et al.*, 2010). To characterize the canopy structure and physical properties, RTMs have also been used to invert the waveform (Koetz *et al.*, 2006). The canopy component of the waveform can be defined as the product of the fractional cover at the zenith of the reflected ALS signal and the volumetric backscattering coefficient of the canopy while the ground component can be defined as the product of the gap fraction and the volumetric backscattering coefficient of the ground (Armston *et al.*, 2011). By assuming that the respective volumetric backscattering coefficients are constant within a local area, the fractional cover may be estimated (Armston *et al.*, 2011).

By modelling the waveform as a series of Gaussian components, information can be derived about the position, amplitude (corresponding to the intensity value), and width of each echo. If reference data are available for calibration, the cross-section of each echo may be derived (Wagner *et al.*, 2006). By observing that the total area of collision must be equal to the footprint area, it is possible to calculate the cross-section of subsequent echoes from the first echo (Wagner *et al.*, 2008). Information about the cross-section is useful for vegetation classification since the cross-section of the vegetation echoes is generally smaller than that of the ground echoes and the cross-section of the forest ground echoes is generally larger than the total cross-section of the canopy echoes (Wagner *et al.*, 2008). The amplitude and the echo width may also be used directly for tree species classification combined with the number of echoes from the canopy (Heinzel *et al.*, 2010). However, the echo width is not included in the current discrete return LAS format, which makes it impossible to use data in that format for analyses including the echo width.

The forest structure may also be described from clustering in three dimensions of ALS returns to delineate tree crowns and understory separately (Barilotti *et al.*, 2008). The structure of the dominant tree layer has been described from a normalized digital surface model (nDSM; i.e., a raster where the value of each raster cell is the maximum height above the DEM of the ALS returns within the raster cell) by delineating convex objects of the canopy separated by concave areas using an edge-based segmentation (Höfle *et al.*, 2008). The approach was to let each tree be represented by one or several segments. The ALS returns originated from decomposed waveform ALS data. The echo width and backscatter cross-section of the ALS returns were related to different deciduous tree species.

Lower vegetation

Lower vegetation such as grass and herbs are of interest in forest areas as well as in agricultural landscapes and areas with floodplain vegetation (Huthoff, 2007). The use of ALS data to study lower vegetation layers has not yet been thoroughly investigated. Cobby *et al.* (2001) used segmentation based on the standard deviation of ALS data in 10 × 10 m windows to classify pixels as short or tall vegetation. The short vegetation height (i.e., grass and cereal crops) was estimated as proportional to the logarithm of the standard deviation of ALS data. The root mean square error (RMSE) was 14 cm for short vegetation height and 17 cm for underlying topography. Straatsma & Middelkoop (2007) used the 95th percentile of the laser returns to estimate the vegetation height and the percentage of laser returns falling within the height interval of the vegetation to estimate density for herbaceous vegetation in the lower Rhine floodplain. To identify the alpine or arctic tree line, a classification scheme can be used to classify laser returns as shrubs and trees or open land (Rees, 2007). The fraction of open land may then be estimated as well as the average size of each patch of shrubs and trees or open land. The occurrence of small trees in a forest-tundra ecotone may be estimated from the fraction of ALS returns above a height threshold (Næsset & Nelson, 2007; Thieme *et al.*, 2011) or with regression models based on height and density measures derived from the ALS data in raster cells (Nyström *et al.*, 2012). ALS data from different acquisitions have been calibrated with histogram matching to analyse the change over time of low vegetation from multi-temporal ALS data (Nyström *et al.*, 2011).

1.2.3 Classification of vegetation using intensity data

Intensity values are available also for discrete return ALS data (i.e., the amplitudes of the returns). The intensity data provide an additional possibility to characterize vegetation and estimate ecological variables (Ussyshkin & Theriault, 2011). A high negative correlation has been reported between the mean canopy cover and First Return Intensity in Canopy stratum (FRI_C) as well as a high positive correlation between mean grass cover and FRI_C from ALS data with a wavelength of 1064 nm (Miura & Jones, 2010). In other words, sparse canopies resulted in lower intensity values of first returns. First Return Intensity in Ground stratum (FRI_G) was positively correlated with mean canopy cover and the amount of fallen trees, which was explained as dense canopies being correlated with fallen trees in the study area and fallen trees resulting in higher intensity values since the light was reflected against solid surfaces. Korpela (2008) classified understory lichen vegetation from the intensity values of discrete return ALS data with a wavelength of 1064 nm. The intensity values were calibrated using a so-called normalization process based on natural target surfaces (e.g., gravel and a grass field) to minimize the influence of the varying distance from the scanner and automatic gain control, which improved the separability of lichens from other surfaces. The energy losses through a canopy have been modelled for discrete return ALS data by using detailed field data including measurements of tree crowns and mapping of the understory (Korpela *et al.*, 2012). The probability of receiving a return from the understory was smaller for a pulse that had already produced a return from the overstory. Compensation for transmission losses was not possible for the intensity values of returns from the understory (Korpela *et al.*, 2012). However, waveform ALS data may be useful for this.

1.2.4 Area-based methods versus individual tree methods

Most of the currently used area-based methods only consider the vertical distribution of the ALS data. The vertical distribution of ALS data might be similar, for example, for a single-layered forest stand and for a multi-layered forest stand. The ALS data have an obvious 3D structure that contains information about the tree crowns. To make use of this, analysis of the 3D structure or surface models derived from the ALS data is an attractive option. This has so far mostly been done using individual tree methods where individual tree crowns (ITC) are delineated from the ALS data.

1.3 Individual tree methods for airborne laser scanning

Individual tree methods are algorithms to delineate tree crowns from high density ALS data and estimate stem attributes and lists of trees based on the delineated tree crowns. Individual tree crowns can also be delineated from high resolution digital aerial images (e.g., Hirschmugl *et al.*, 2007). The height and shape of the top of the canopy can be derived from ALS data. If the measurement density is high enough, individual tree crowns can be delineated from the ALS data and the height, diameter, and shape of the tree crowns can be derived. Many modern forest management planning systems require information at individual tree level (Söderbergh & Ledermann, 2003; Backeus *et al.*, 2005; Kärkkäinen *et al.*, 2008) or at least about the DBH distribution in forest stands (Maltamo *et al.*, 2007). For the purpose of forest management planning and forecasting, unbiased estimates are also essential.

1.3.1 Surface model methods

Automatic delineation of individual tree crowns from ALS data can be done by deriving a surface model representing the top of the canopy and identifying local maxima in the surface model as tree tops. A common approach is to derive an nDSM by defining a raster where the value in each raster cell is equal to the height of the top of the canopy above the ground. The ground level is represented by a DEM derived from the ALS data. The raster cell size is usually 0.25×0.25 to 0.5×0.5 m depending on the density of the ALS data. The nDSM may be derived from the maximum height of the ALS returns within each raster cell (Hyyppä & Inkinen, 1999) or by interpolation of the highest ALS returns (Persson *et al.*, 2002). The surface model is filtered to remove small variations in the tree crowns and local maxima are identified as tree tops. The surface model is usually delineated by region growing around the local maxima (Hyyppä *et al.*, 2001; Solberg *et al.*, 2006) or by watershed segmentation (Persson *et al.*, 2002). Other delineation approaches are, for example, spatial wavelet analysis (Falkowski *et al.*, 2006) or detection of cone shaped objects using the Hough transform (Van Leeuwen *et al.*, 2010).

A priori knowledge about the relative proportions of tree crowns may be used to control the shapes of the delineated segments to avoid too elongated horizontal segments (Hyyppä *et al.*, 2001), to fit a parabolic surface to the height of each delineated segment and select the size of the smoothing filter that results in a small sum of residuals (Persson *et al.*, 2002), or to select the size of the window where the local maximum is detected based on tree height (Popescu *et al.*, 2002) and tree species (Popescu & Wynne, 2004). Rasterization of ALS data will result in a loss of information since the accurate coordinates of the ALS returns are approximated into raster cell positions and the value in each raster cell is a combination of several ALS returns. Following Axelsson (1999), the original data should be used as long as possible in the filtering and modelling process. This can be achieved by using the correlation between generalized ellipsoids of revolution (GER) and the ALS returns (Holmgren & Wallerman, 2006; Holmgren *et al.*, 2012). A correlation surface (CS) can be derived by placing the centre of a GER in each raster cell, selecting the radius of the GER with the maximum correlation, and setting the raster cell value to the maximum found correlation. Delineation of individual tree crowns may then be done from the CS using, for example, watershed segmentation. Delineation from surface models can identify most of the trees in the dominant tree layer of coniferous-dominated hemi-boreal and boreal forests, but only a smaller fraction of the trees below the dominant tree layer can be identified in this way (Persson *et al.*, 2002; Solberg *et al.*, 2006).

1.3.2 Three-dimensional methods

Since parts of the laser light can pass through gaps in the canopy, the ALS data include measurements of surfaces below the dominant tree layer. This makes it possible to derive a DEM also in dense forests (Kraus & Pfeifer, 1998; Axelsson, 1999; Harding, 2009). Additionally, measurements may originate from small trees and shrubs below the dominant tree layer. These properties may be used to delineate individual tree crowns in three dimensions from ALS data. The delineation may be done with k-means clustering where the initial values for the clustering are derived from local maxima in an nDSM or by other means of identifying tree tops from the ALS data (Morsdorf *et al.*, 2003; Gupta *et al.*, 2010). The accuracy of clustering methods compared to delineation from surface models has only been validated in a few studies, but current results indicate that delineation from a surface model using *a priori* knowledge about tree crowns may result in equal or higher accuracy than k-means clustering in three dimensions (Vauhkonen *et al.*, 2011). The delineation may also be done by region growing from the tree tops and downwards of ALS returns (Lee *et al.*, 2010) or voxels (Vaughn *et al.*, 2012). Another approach is to first determine an approximate number of stems by clustering of the ALS data below the dominant tree layer and then use the estimated stem number for delineation of individual tree crowns with a normalized cut algorithm applied to voxels derived from the ALS data (Reitberger *et al.*, 2009). Normalized cut divides data into groups based on the total feature dissimilarity between the different groups as well as the total feature similarity within the groups (Shi & Malik, 2000). The features were the mean intensity values and mean width of echoes from calibrated waveform ALS data within each voxel. The normalized cut has resulted in a larger fraction of identified trees, especially for trees below the dominant tree layer, and a slight increase in erroneously delineated trees compared to watershed segmentation of an nDSM (Reitberger *et al.*, 2009).

1.3.3 Tree species classification

A great advantage of individual tree methods is that tree species classification of individual trees may be done from the ALS data, which is particularly useful for field plots with a mixture of tree species. Tree species classification of individual tree crowns delineated from surface models derived from discrete return ALS data can be done based on the first moments of the height and intensity data distributions within each tree crown segment (Brandtberg *et al.*, 2003) as well as other variables derived from the height and intensity data distributions, from the fraction of first returns, and from a parabolic surface fitted for each tree crown segment (Holmgren & Persson, 2004), which has also been confirmed by later studies (Donoghue *et al.*, 2007; Ørka *et al.*, 2009). By describing the extent of the tree crowns with alpha shape metrics, additional variables can be derived to both classify tree species and estimate DBH (Holmgren *et al.*, 2008b; Vauhkonen *et al.*, 2008). This kind of analysis utilizes more details of the ALS data together with the knowledge of the shape of tree tops and tree crowns (Holmgren & Persson, 2004; Vauhkonen *et al.*, 2009). Tree species classification of individual trees has also been done with good results from a combination of discrete return ALS data and multi-spectral aerial images (Holmgren *et al.*, 2008b).

Tree species classification may also be done from waveform ALS data. Since the waveform data describe the reflected light in more details, it is possible to derive the intensity value and width of the echoes and also the backscatter cross-section if calibration data are available. Tree species classification of individual tree crowns delineated from surface models is improved by including variables derived from the echo width, the backscatter cross-section, and the total number of echoes within the tree crowns (Reitberger *et al.*, 2008b; Hollaus *et al.*, 2009b; Heinzel & Koch, 2011). Tree species classification may also be done for individual tree crowns delineated in three dimensions. So far, this has been done for waveform ALS data based on intensity value and echo width (Reitberger *et al.*, 2008a). Additionally, the Fourier transform may be applied to the waveform to derive information about the distribution of returned intensity values along the pulse, which is related to the positions of branches in the tree crowns. This approach has been shown to improve the tree species classification (Vaughn *et al.*, 2012).

1.3.4 Estimation of stem attributes and tree lists

Individual tree methods could produce lists of tree stems with associated positions and tree heights for most of the dominant and subdominant trees in coniferous hemi-boreal and boreal forests. If field reference data from the laser scanned area are available, statistical models or pattern recognition methods can be created to estimate variables relevant for forest management planning such as DBH and stem volume (Persson *et al.*, 2002; Vauhkonen *et al.*, 2010). However, individual tree methods often fail to identify trees below the dominant tree layer and trees standing close together (Persson *et al.*, 2002; Reitberger *et al.*, 2009). Hence, the result is likely to be an underestimation of the stem density and stem volume per area unit when aggregated over forest stands or other area units.

1.3.5 Aggregation to plot or stand level

If the individual tree method does not identify all trees, the result will be biased if the estimates are simply aggregated over field plots or forest stands. The use of individual tree methods is limited without taking this into consideration. The failure of individual tree methods to identify all trees has been addressed with several approaches. Maltamo *et al.* (2004) fitted a theoretical expected tree size function to the distribution of tree heights estimated with an individual tree method. The theoretical function was used as a complement to predict the number of trees with lower heights and derive a more complete tree size distribution. The tree crown delineation resulted in an underestimation of stem density (RMSE 74%, bias -61%) and stem volume (RMSE 25%, bias -24%), but estimation using an expected tree height function reduced the error (stem density RMSE 49%, bias -6%; stem volume RMSE 16%, bias -8%) for field plots with approximately 100 trees each (plot size 625–1600 m^2). Hyyppä *et al.* (2005) suggested delineation of tree clusters rather than individual trees from ALS data. However, it was also noted that estimation of stem volume from segments containing several trees required further investigation. Statistical approaches have been used for this purpose. The properties of the delineated segments may be used to estimate the number of trees per segment and associated stem attributes based on field reference data including tree positions and stem attributes. The results from different approaches indicate that such statistical analysis may improve the accuracy and in some cases even outperform area-based methods (see Discussion; Flewelling, 2008; Lindberg *et al.*, 2008; Breidenbach *et al.*, 2010a; Holmgren *et al.*, 2010; Lindberg *et al.*, 2010b).

1.3.6 Co-registration with field reference data

The extents of the delineated segments represent properties of the trees such as height and crown diameter. One approach to estimate stem attributes from the delineated segments has been to assume that the tree heights can be measured directly from the delineated segments (Hyyppä *et al.*, 2008) and that the DBH can be calculated from the tree height and the crown diameter using regional allometric functions (Vastaranta *et al.*, 2012). However, the accuracy of such estimations is limited by the imprecision of the allometric functions when applied to varying stem density and silvicultural history (Villikka *et al.*, 2008; Vauhkonen *et al.*, 2010). Due to this, field reference data including tree positions and stem attributes at the individual tree level are preferable. This is usually achieved by allocating field plots in the forest area and measuring the position and DBH of all trees and the height of a subsample of trees. By co-registering the individual tree crowns delineated from the ALS data and the field-measured trees, models can be created to estimate stem attributes. Common models are regression models (Persson *et al.*, 2002) but also random forest (Yu *et al.*, 2011) and k-MSN (Vauhkonen *et al.*, 2010).

The co-registration must be accurate enough to reduce errors (Gobakken & Næsset, 2009), preferably with sub-metre accuracy. However, field data with such accurate positions are not always available, in particular due to errors in GPS measurements below a canopy. A number of approaches have been developed for automatic co-registration of poorly positioned datasets consisting of individual tree positions. The positions of individual trees identified from remotely sensed data may be used to map the tree positions in field whereupon other points can be positioned using triangulation (Korpela *et al.*, 2007). Individual tree crown segments may be associated with field-measured trees using Voronoi tessellations (Flewelling, 2008). The position of the field plot may be determined by minimizing the sum of the difference between the heights of field-measured trees and the height of an nDSM at the tree positions within a specified search window, taking into account if the tree belongs to the dominant tree layer or a lower canopy layer (Dorigo *et al.*, 2010). Additionally, the effect of angle count sampling field inventory can be taken into account (Dorigo *et al.*, 2010). Position images of field-measured trees and individual tree crowns can be cross-correlated and the position of the field plot may be determined by maximizing the correlation within a specified search window (Olofsson *et al.*, 2008).

The positions of individual trees can be determined in field by measuring the positions of the trees relative to the field plot centre and measuring the position of the field plot centre with a high precision GPS. The tree positions relative to the field plot centre may be determined from manual measurements of the direction and distance of each tree (Yu *et al.*, 2010) or with automated methods such as distance measurements to three known positions close to the field plot centre using an ultrasound instrument (Lämås, 2010). Even though electronic equipment can be used to save the measurements automatically, the field workers still have to measure each tree individually. Terrestrial laser scanning is an additional option, which provides a possibility for automated measurements of tree positions and details of the stems.

1.4 Terrestrial laser scanning

The 3D coordinate measurements from TLS can be used to derive information about tree stems, foliage, and branches of trees and shrubs. This provides possibilities for automated measurements of forest stands for forest management planning as well as for ecological studies. This may be used for detailed measurements at selected sites of special interest, for estimation using a statistical sampling approach, or for collection of training data for wall-to-wall remotely sensed data. An important use of TLS data is for estimation of vegetation structure and canopy volume profiles (e.g., Lovell *et al.*, 2003; Henning & Radtke, 2006b; Hosoi *et al.*, 2010). However, concerning applications for TLS, the emphasis of this thesis lies on estimation of stem properties to use as training data for ALS data.

1.4.1 Methods for three-dimensional modelling of tree stems

A common way to estimate tree positions and stem diameters from TLS data is to first find approximate tree positions and stem diameters from the data, select laser reflections in narrow cylinders based on the approximate values, and finally fit circles along the stems. The tree positions and diameters are determined most efficiently from the lower part of the stems where less foliage obscures the measurements. Hence, a DEM must first be derived from the TLS data to determine the height above the ground of the laser reflections (Thies & Spiecker, 2004). Approximate tree positions and diameters can then be found using manual detection (Hopkinson *et al.*, 2004), skeletonization (Gorte & Pfeifer, 2004), a clustering algorithm (Bienert *et al.*, 2007; Király & Brolly, 2007; Maas *et al.*, 2008), or the Hough transform (Aschoff *et al.*, 2004). Circles can be fitted along the stems with least squares regression from TLS data selected based on the approximate tree positions and stem diameters (Pfeifer *et al.*, 2004; Watt & Donoghue, 2005). To filter out laser reflections not originating from the stems, an iterative process may be used by fitting a circle, removing laser reflections with too large residuals, and re-fitting the circle (Henning & Radtke, 2006a). The laser reflections may also be filtered by fitting a plane for the nearest neighbours of each laser reflection and removing laser reflections where the plane fitting accuracy is below a certain threshold based on the assumption that the planes will fit better to laser reflections from the tree stems and worse for laser reflections from the foliage (Pfeifer *et al.*, 2004).

Additional information about the stems may be derived with more complex models. Wezyk *et al.* (2007) modelled tree stems from TLS data by fitting convex hulls to the laser reflections and estimating DBH and basal area from the convex hulls. Thies *et al.* (2004) used TLS data collected at multiple positions around the centre of a field plot to model tree stems with overlapping cylinders. The cylinders were fitted from the root of the tree and upwards along the stem until a preselected maximum RMSE was exceeded.

1.4.2 Potentials of terrestrial laser scanning in forest inventory

TLS could be used to collect information about tree stems in the field that is measured manually today. The time spent on measuring the stem diameters and in some cases tree positions manually could be used for collecting other data in the field plots. Additionally, TLS offers the potential to collect information about stems that is currently not measured. Forest inventories often include assessments of the quality of a subsample of trees and the fertility of the field plots. However, a conventional field inventory does not assess the quality of all trees in the field plots and includes no information about stem forms or taper curves and the positions of branches since this is almost impossible to achieve with manual measurements.

TLS offers the potential to obtain detailed information about the stems. It can be expected that forest inventories using TLS will provide timber quality of standing trees with high accuracy (Thies & Spiecker, 2004). Pfeifer & Winterhalder (2004) created detailed models of tree stems and branches by estimating the direction of each branch and fitting closed B-spline curves along the stems and branches. This information is almost impossible to achieve with manual measurements in a conventional forest inventory.

1.4.3 Combination of airborne and terrestrial laser scanning

The combination of data from TLS and ALS offers the potential to implement a forest inventory system with minimal need for manual measurements. The tree stems estimated from TLS data may be used as training data for models to estimate stem attributes from ALS data. For this purpose it might not be necessary to find all trees in a given area from the TLS data as long as the selection is representative of all trees.

The combination has been used to measure canopy structure (Lovell *et al.*, 2003; Hilker *et al.*, 2010; Hosoi *et al.*, 2010). TLS and ALS data have also been co-registered at the tree level for the purpose of forest management planning (Lindberg *et al.*, 2010a; Lindberg *et al.*, 2011). Stem lists derived from TLS and ALS have been linked using properties of the stems estimated from TLS data assuming high precision positioning in the field (Fritz *et al.*, 2011). However, since GPS positions measured below a canopy are less accurate, the positions of the data collected in field must in practice be adjusted, which may be done by correlation of tree position images (Olofsson *et al.*, 2008). When using TLS data for the field measurements, the co-registration must also take into account the zones in the TLS data that are obscured from the scanner (Lindberg *et al.*, 2010a; Lindberg *et al.*, 2011).

2 Objectives

The objective of this thesis is to further develop the methods to estimate information about individual trees and canopy structure from laser scanning data. This includes further development of methods for 3D modelling of tree crowns from ALS data and tree stems from TLS data, development of statistical methods for estimation of stem attributes from individual tree crowns delineated from ALS data, development of methods for combination of TLS and ALS data at tree level, and development of methods for estimation of vertical vegetation structure from ALS data. The specific objectives for papers I-IV are

- I To develop and validate a method to estimate a list of individual trees with associated stem attributes such as tree height, DBH, and stem volume. The most important requirement is that the tree list should result in unbiased estimates when aggregated over an area, for example, a forest stand. The idea is to use the information that can be derived about individual tree crowns from high density ALS data and calibrate these results with estimates from area-based methods at plot level.
- II To develop and validate methods to delineate tree crowns from ALS data using more *a priori* knowledge and to estimate individual trees and associated stem attributes from the delineated tree crowns with a statistical model. The idea is to use the information about the dominant tree layer from segmentation of a surface model and then use 3D methods to derive information about lower trees. The requirements for unbiased estimates are the same as for paper I.
- III Firstly, to develop and validate a method to automatically estimate tree positions and DBH from TLS data. Secondly, to develop a method to automatically link the tree stems found from the TLS data with tree crown segments delineated from ALS data and compare the accuracy of

ALS estimates trained with TLS data with the corresponding estimates trained with manual field measurements.

IV To develop and validate automated methods to estimate vertical vegetation structure from ALS data to represent the shrub layer and one or several tree layers and to compare different methods of estimating vegetation volume profiles from waveform ALS data and discrete return ALS data.

3 Material and methods

3.1 Material

3.1.1 Study areas

The study areas used in this thesis were located in boreal and hemi-boreal forest in Sweden (figure 2). The dominant tree species were Norway spruce (*Picea Abies*), Scots pine (*Pinus Sylvestris*), and birch (*Betula spp.*).

3.1.2 Field data

Field plots were allocated in the study areas (table 1).

Table 1. *Study areas used in the papers.*

Paper	Area	Lat Long	Nature types	Field plots	Number of field plots
I	Fiskåvattnet	64° N, 14° E	Boreal forest near the tree line	Circular, 6 and 8 m radius	179
II	Krycklan	64° N, 19° E	Boreal forest	Circular, 12 m radius	105
III	Remningstorp	58° N, 13° E	Hemi-boreal forest	Rectangular, 80 × 80 m	6
IV	Remningstorp	58° N, 13° E	Hemi-boreal forest and pasture land	Circular, 12 m	68

Figure 2. Map over Sweden and the study areas Fiskåvattnet, Krycklan, and Remningstorp.

The positions of the field plots were measured using a high precision GPS. All trees with a DBH larger than a defined limit within the field plots were measured using a calliper and the height was measured for a subsample of trees. The positions of the trees were measured relative to the GPS positions using an ultra-sound device (Lämås, 2010) or a total station. The stem volume was calculated for the subsample of trees where the height was measured in field (e.g., Brandel, 1990). To estimate the tree height and the stem volume of all trees, species specific regression models were created for tree height and stem volume as functions of DBH.

For paper IV, the extents of the crowns of all trees and shrubs higher than 3 dm were also measured. The measurements were used to model vegetation volume profiles as the sum of the volume of all crowns in 1 dm height intervals above the ground.

3.1.3 Airborne laser scanning data

The average measurement density of the ALS data was 10 emitted pulses m^{-2} (paper I), 15 returns m^{-2} (paper II), 30 returns m^{-2} (paper III), and 7 emitted pulses m^{-2} (paper IV). The first and last returns for each pulse were recorded. Laser returns were classified as ground or non-ground using a progressive triangular irregular network (TIN) densification method (Axelsson, 1999; Axelsson, 2000) implemented in the TerraScan software (Soininen, 2004), and the ground returns were used to derive a DEM. For paper IV, waveform data were also recorded.

3.1.4 Terrestrial laser scanning data

For paper III, TLS data were collected using an Optech ILRIS-3D scanner with a 40º × 40º field of view. One centrally located scanner position was used in each field plot. The complete 360º scenes in the horizontal plane were collected by scanning one scene at a time, rotating the scanner, and rectifying the scenes against each other

3.2 Methods

The creation of the models used to estimate forest variables from the ALS data and the validation of the estimated forest variables were done with leave-one-out cross-validation for one field plot at a time for all papers.

3.2.1 Estimation of tree lists from airborne laser scanning by combining single-tree and area-based methods (Paper I)

Paper I describes a new method to estimate lists of trees from individual tree crown segments delineated from ALS data. The tree crown segments were delineated from an nDSM derived from ALS data and features were extracted from the properties of the segments. The number of trees in each segment as well as mean values of the DBH, stem volume, and tree height in each segment was estimated based on the extracted features. The estimated number of trees was assigned to each segment and the estimated forest variables were assigned to the trees, resulting in a tree list for each field plot. As a second step, the tree list was calibrated using target distributions of tree height and DBH estimated at plot level. If the number of tree candidates was too large according to the target distribution, the corresponding number of trees was excluded from the list. If the number of tree candidates was too small, the corresponding number of trees was added to the list from a field database. The total number of trees was chosen to make the total stem volume in the field plot equal to the stem volume estimated from a regression model at plot level.

3.2.2 Estimation of tree lists from airborne laser scanning using model-based clustering and k-MSN imputation (Paper II)

Individual tree crowns were delineated from the ALS data based on geometric tree crown models. A CS was derived where each raster cell value was set to the maximum correlation found using tests with geometric tree models. The correlation was calculated between z-values of laser returns and h-values of generalized ellipsoids for the x- and y-values of the laser returns. The CS was smoothed and delineated with watershed segmentation around local maxima. In a second step, a model-based clustering approach based on k-means clustering was used to divide the ALS data into clusters in three dimensions. The segments from the CS were used as fixed cluster centres. Additionally, four times as many flexible cluster centres were initially placed at regular distances in the field plot. The flexible cluster centres were allowed to move freely during the clustering and the fixed cluster centres were allowed to move vertically with restrictions but were fixed in the horizontal plane. Additionally, the clustering was weighted to make ALS returns assigned to one segment more difficult to assign to a cluster corresponding to a different segment and to make ALS returns close to the top of the canopy more difficult to assign to a flexible cluster. A parabolic surface was fitted for each flexible cluster and the distance measure for the clustering included the distance of a return above the parabolic surface. Finally, clusters were joined based on the vertical alignment and the distance between the cluster centres. The field-measured trees were linked to the resulting clusters. Trees were imputed to the clusters based on features extracted from the spatial distribution of ALS data in each cluster. As a comparison, the field-measured trees were linked to the segments and trees were imputed to the segments based on features extracted from the segments.

3.2.3 Estimation of stem attributes using a combination of terrestrial and airborne laser scanning (Paper III)

Stem positions and diameters were estimated from TLS data in an automated processing chain. Initial positions and diameters were estimated using an adapted Hough transform of stem projection images derived from the density of laser reflections in a height span of 1-2 m above the ground. The initial estimations were used to select laser reflections in a cylinder for each tree stem and circles were fitted along the stem. Linear functions were fitted for the position and diameter of the fitted circles, approximating the tree stem with a tilted cone. The linear functions were used to select a new set of laser reflections and circles were fitted along the tree stem again. Finally, the DBH was estimated by fitting a linear function for the diameters and calculating the diameter at 1.3 m above the ground. The stem positions were co-registered and linked with tree crown segments delineated from a CS derived from ALS data based on geometric tree crown models. The co-registration masked the obscured zones in the field plot depending on where trees were found in the TLS data. The linked stems were used as training data for regression models to estimate DBH, tree height, and stem volume. The accuracy of the estimated stem attributes were compared with stem attributes estimated from ALS data using manually measured trees as training data.

3.2.4 Estimation of 3D vegetation structure from waveform and discrete return airborne laser scanning data (Paper IV)

Paper IV describes new automated methods to estimate vertical vegetation structure from ALS data. In one method the waveform ALS data were used directly (direct waveform (a)) and in a second method care was taken to first compensate for the shielding effect of higher vegetation layers on reflections from lower layers based on the Beer-Lambert law (normalized waveform (b)). ALS waveform profiles were derived by summing the intensity values of the ALS waveforms in 1 dm height intervals for direct waveform (a) and normalized waveform (b). In a third method returns were derived from the ALS waveform using the Expectation–Maximization (EM) algorithm (waveform points (c)) and in a fourth method conventional, discrete return ALS data from the laser scanning system were used (system points (d)). ALS point profiles were derived by summing the number of ALS returns in 1 dm height intervals for waveform points (c) and system points (d).

Vegetation volume profiles were derived in 1 dm height intervals from the field data assuming that each tree crown was an ellipsoid and each shrub was a half-ellipsoid standing on the ground. The vegetation volume profile was used rather than biomass profiles or LAD since it was feasible to measure in a large number of field plots. The total vegetation volume (defined as the sum of the vegetation volume in each field plot) was estimated from the ALS profiles based on the Beer-Lambert law. Vegetation volume profiles were estimated by rescaling the ALS profiles with the estimated total vegetation volume. The vegetation volume in height intervals ≤30 dm, ≤100 dm, and >100 dm was estimated as the sum of the vegetation volume profile in those intervals.

3.2.5 Validation

The validation was done using RMSE (equation 4) and bias (equation 5)

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n}(\hat{Y}_j - Y_j)^2}{n}} \quad (4)$$

$$bias = \frac{\sum_{j=1}^{n}(\hat{Y}_j - Y_j)}{n} \quad (5)$$

where $\hat{Y}_j$ is the estimated value and Y_j is the true value of a forest variable in plot *j* or a stem attribute of tree *j,* and *n* is the number of plots or trees, respectively. The error index (EI; Reynolds *et al.*, 1988) was calculated for the distributions of tree heights, DBH, and basal area as well as the vegetation volume profiles (equation 6)

$$EI = \frac{1}{N_T}\sum_{k=1}^{m}\left|\hat{F}_k - F_k\right| \quad (6)$$

where $\hat{F}_k$ is the estimated value in interval *k*, F_k is the true value in interval *k*, *m* is the number of intervals, and N_T is the sum of F_k over all intervals.

4 Results

The results from the four papers are summarized in the following sections.

4.1 Estimation of tree lists from airborne laser scanning by combining single-tree and area-based methods (Paper I)

Estimation of one tree per delineated segment resulted in a negative bias for the stem volume and stem density when aggregating the tree lists to field plot level (table 2; 1a). Estimation of a number of trees with stem attributes per segment improved the accuracy, and the bias of the estimated stem volume was close to zero when aggregating the tree lists to field plot level (table 2; 1b). Estimation with an area-based method at field plot level (i.e., estimation of distributions and no tree lists) resulted in very small bias for stem volume and stem density (table 2; 2). However, calibration of the tree lists with the area-based estimates resulted in tree lists with almost the same accuracies as the area-based estimates when aggregating the tree lists to field plot level (table 2; 3a and 3b).

Table 2. *Plot-level RMSE and bias of stem volume and stem density estimates aggregated over field plots using the methods: 1a. Estimation at the individual tree level, 1b. Estimation at the individual tree level including estimation of the number of trees per segment, 2. Estimation at the field plot level, 3a. Calibration of tree candidate list from results at the field plot level, 3b. Calibration of tree candidate list including estimation of the number of trees per segment from results at the field plot level.*

Method	Stem volume (m^3ha^{-1})		Stem density (ha^{-1})	
	RMSE	Bias	RMSE	Bias
1a. Individual tree level	35 (36%)	-14 (-14%)	595 (52%)	-403 (-35%)
1b. Individual tree level + estimation of the number of trees per segment	33 (34%)	-2 (-3%)	515 (45%)	-208 (-18%)
2. Area-based, field plot level	35 (36%)	0 (0%)	421 (37%)	-33 (-3%)
3a. Calibration of 1a with 2	36 (37%)	4 (4%)	421 (37%)	-34 (-3%)
3b. Calibration of 1b with 2	36 (37%)	2 (2%)	421 (37%)	-36 (-3%)

The error indexes of the estimated tree lists were smaller when estimating one tree per delineated segment (table 3; 1a) than when estimating a number of trees with stem attributes per segment (table 3; 1b). Estimation with an area-based method at field plot level resulted in the smallest error indexes (table 3; 2). Calibration with the area-based estimates improved the error indexes for both the tree lists from one tree per delineated segment (table 3; 3a) and the tree lists from a number of trees per segment (table 3; 3b).

Table 3. *Mean error index (unitless) for the distributions of tree heights, DBH, and basal area at the field plot level using the methods: 1a. Estimation at the individual tree level, 1b. Estimation at the individual tree level including estimation of the number of trees per segment, 2. Estimation at the field plot level, 3a. Calibration of tree candidate list from results at the field plot level, 3b. Calibration of tree candidate list including estimation of the number of trees per segment from results at the field plot level.*

Method	Error index		
	Tree height	DBH	Basal area
1a. Individual tree level	0.98	0.97	0.90
1b. Individual tree level + estimation of the number of trees per segment	1.09	0.99	0.92
2. Area-based, field plot level	0.82	0.76	0.69
3a. Calibration of 1a with 2	0.96	0.92	0.89
3b. Calibration of 1b with 2	0.96	0.93	0.89

4.2 Estimation of tree lists from airborne laser scanning using model-based clustering and k-MSN imputation (Paper II)

The accuracy of the stem volume was higher for tree lists estimated with k-MSN imputation from the model-based clustering (table 4; 2) than for tree lists estimated with k-MSN imputation from delineation of a CS (table 4; 1) when aggregated to field plot level. The accuracy of the stem density was lower for the tree lists estimated from model-based clustering.

Table 4. *Plot-level RMSE and bias of stem volume and stem density estimates aggregated over field plots, using the methods: 1. Delineation of a CS and 2. model-based clustering, both with k-MSN imputation of individual trees.*

Method	Stem volume (m^3ha^{-1})		Stem density (ha^{-1})	
	RMSE	Bias	RMSE	Bias
1. Delineation of a CS followed by k-MSN imputation	45.5 (29.7%)	5.9 (3.8%)	372.9 (32.0%)	22.7 (1.9%)
2. Model-based clustering followed by k-MSN imputation	33.7 (22.0%)	3.8 (2.5%)	388.1 (33.3%)	12.8 (1.1%)

The error indexes were higher for the model-based clustering (table 5; 2) than for delineation of a CS (table 5; 1).

Table 5. *Mean error index (unitless) for the distributions of tree heights, DBH, and basal area at the field plot level using the methods: 1. Delineation of a CS and 2. model-based clustering, both with k-MSN imputation of individual trees.*

Method	Error index		
	Tree height	DBH	Basal area
1. Delineation of a CS followed by k-MSN imputation	0.68	0.64	0.60
2. Model-based clustering followed by k-MSN imputation	0.72	0.68	0.62

The model-based clustering was capable of delineating tree crowns also in the understory below the dominant tree layer (figure 3).

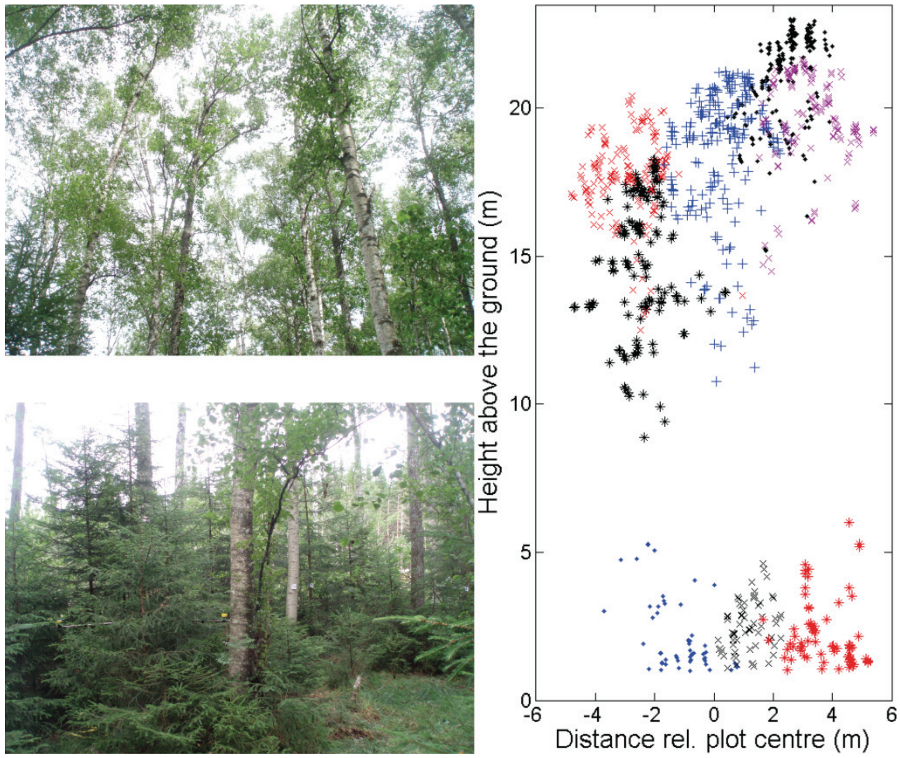

Figure 3. Example of a birch-dominated field plot with understory; photograph from field, upwards view (top left), photograph from field, horizontal view (bottom left), and side view of ALS data with different symbols showing different clusters from model-based clustering (right).

The fraction of field-measured trees that were linked to delineated tree crowns was higher for the model-based clustering than for segmentation of the CS model, especially for trees with smaller DBH in field plots with higher basal area-weighted mean tree height (i.e., trees in the understory below the dominant tree layer; figure 4). However, the model-based clustering also resulted in more segments that could not be linked to any field-measured tree.

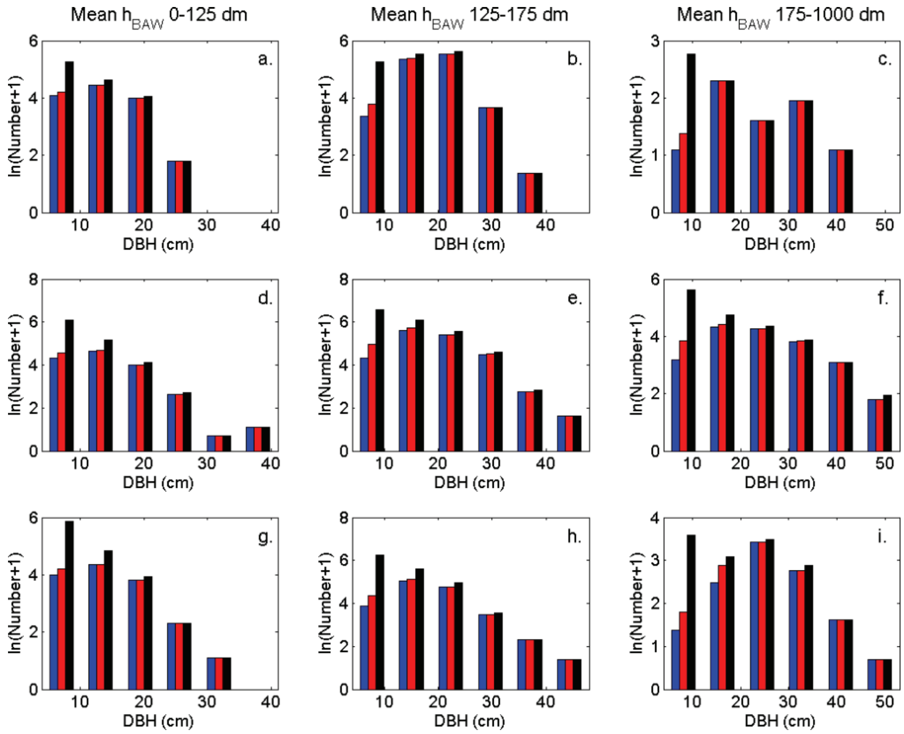

Figure 4. DBH distribution of different strata; pine-dominated (top), spruce-dominated (middle), and mixed or deciduous-dominated (bottom). The black bars are all trees, the red bars are trees that were linked to tree crowns delineated with the model-based clustering, and the blue bars are trees that were linked to tree crowns delineated from the CS.

4.3 Estimation of stem attributes using a combination of terrestrial and airborne laser scanning (Paper III)

The RMSE of the DBH estimated from TLS data was smallest for birch, second smallest for pine, and largest for spruce. The bias was negative for pine, positive for spruce, and close to zero for birch (figure 5).

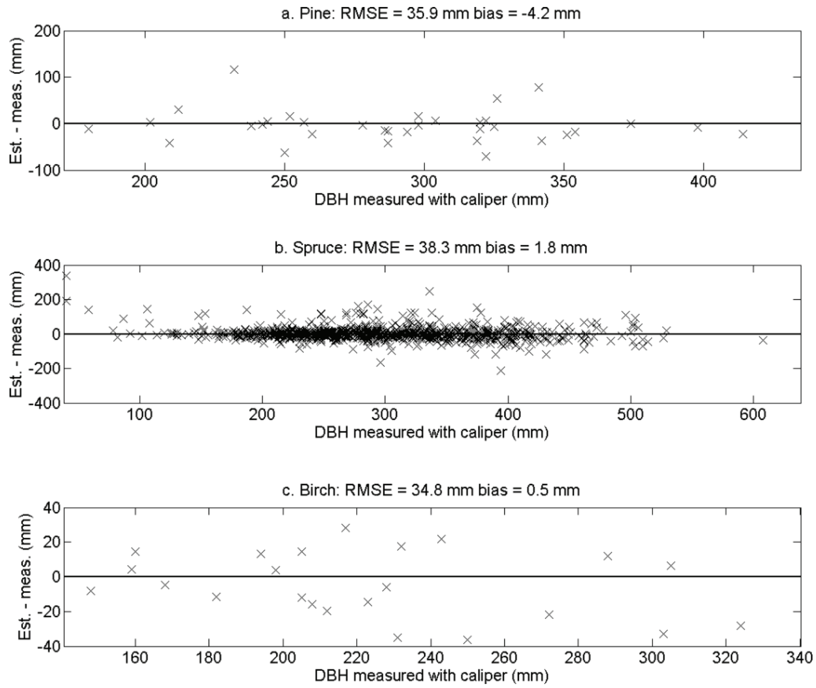

Figure 5. The residuals of DBH estimated from TLS data versus manually measured DBH for pine (a), spruce (b), and birch (c).

A greater fraction of trees with large DBH were linked to tree crowns delineated from ALS data compared to trees with small DBH (figure 6). This was the case both for trees found from TLS data and trees from the manual field inventory.

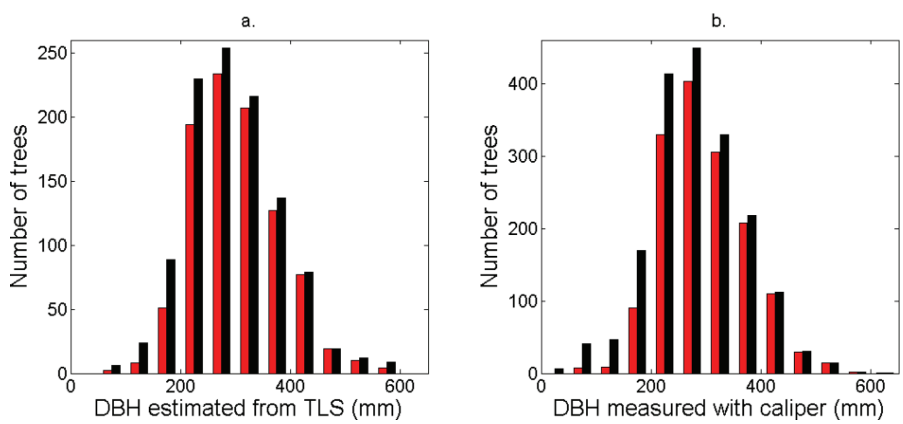

Figure 6. DBH distribution of trees found from TLS (a) and trees from manual field inventory (b). The black bars are all trees and the red bars are trees that were linked to tree crowns delineated from ALS data.

The accuracy of the DBH and stem volume estimated from ALS data when using trees found from TLS data as training data was almost the same as when using trees from the manual field inventory as training data (table 6).

Table 6. *Tree-level RMSE and bias of DBH and stem volume estimated from ALS data for the two different training datasets.*

Training data	Number of trees in training data	RMSE	Bias
DBH		(mm)	(mm)
TLS data	933	46.0 (15.4%)	-1.0 (-0.3%)
Manual field inventory	1508	45.1 (15.1%)	0.4 (0.1%)
Stem volume		(dm3)	(dm3)
TLS data, model based only on spruce trees	723	200.4 (34.6%)	39.7 (6.8%)
TLS data, weighted model based on trees from all species	933	197.4 (34.0%)	19.8 (3.4%)
Manual field inventory, model based only on spruce trees	1411	200.2 (34.5%)	27.4 (4.7%)

4.4 Estimation of 3D vegetation structure from waveform and discrete return airborne laser scanning data (Paper IV)

The RMSE of the total vegetation volume was smallest for the normalized waveform (b), second smallest for the waveform points (c), third smallest for the direct waveform (a), and largest for the system points (d). The bias of the total vegetation volume was also smallest for the normalized waveform (b) and largest for the system points (d) although the bias was very small (figure 7).

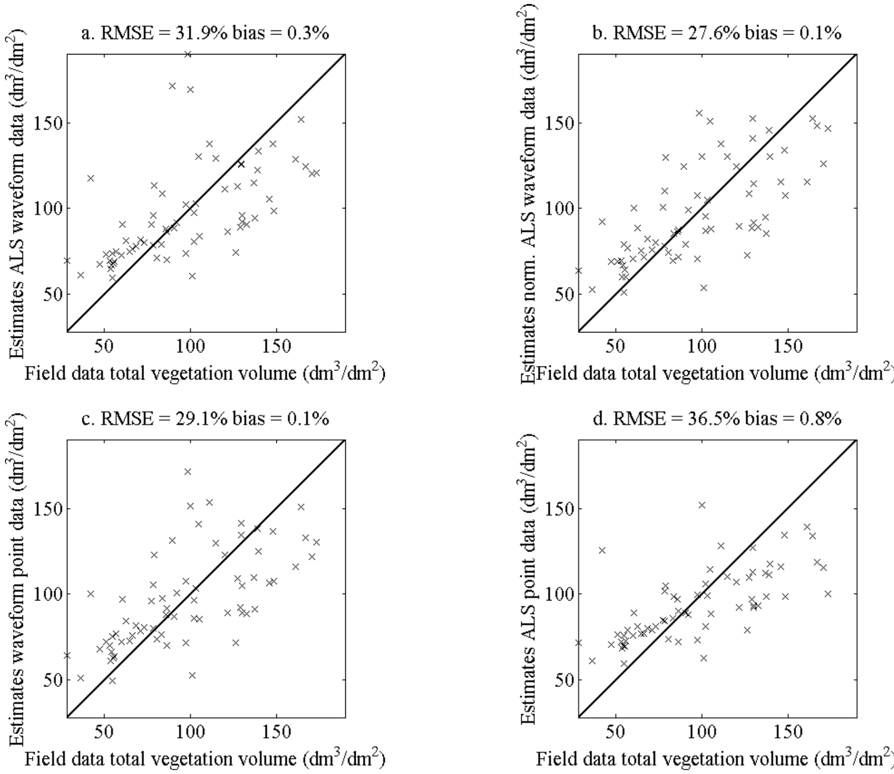

Figure 7. Total vegetation volume estimated from direct waveform (a), normalized waveform (b), waveform points (c), and system points (d) for the 68 field plots. Field plots dominated (≥70% of basal area) by pine are marked 'x', spruce 'o', birch '·', oak '*', other broadleaf '+' and mixed forest 'Δ'.

The mean error index was smallest for the normalized waveform (b) and waveform points (c), second smallest for the direct waveform (a), and largest for the system points (d) (Table 7).

Table 7. *Mean error index (unitless) for the different estimated vegetation volume profiles. Note that the error index is only comparable within each row.*

	Direct waveform (a)	Normalized waveform (b)	Waveform points (c)	System points (d)
Error index original profiles	0.58	0.58	0.54	0.62
Error index mean height adjusted profiles	0.43	0.39	0.39	0.46
Error index profiles with area rescaled to field data	0.50	0.44	0.46	0.52
Error index profiles with area rescaled to field data and mean height adjusted	0.35	0.29	0.30	0.37

The methods developed may be used for estimation of vegetation volume profiles for large areas and transects of vegetation density (figure 8).

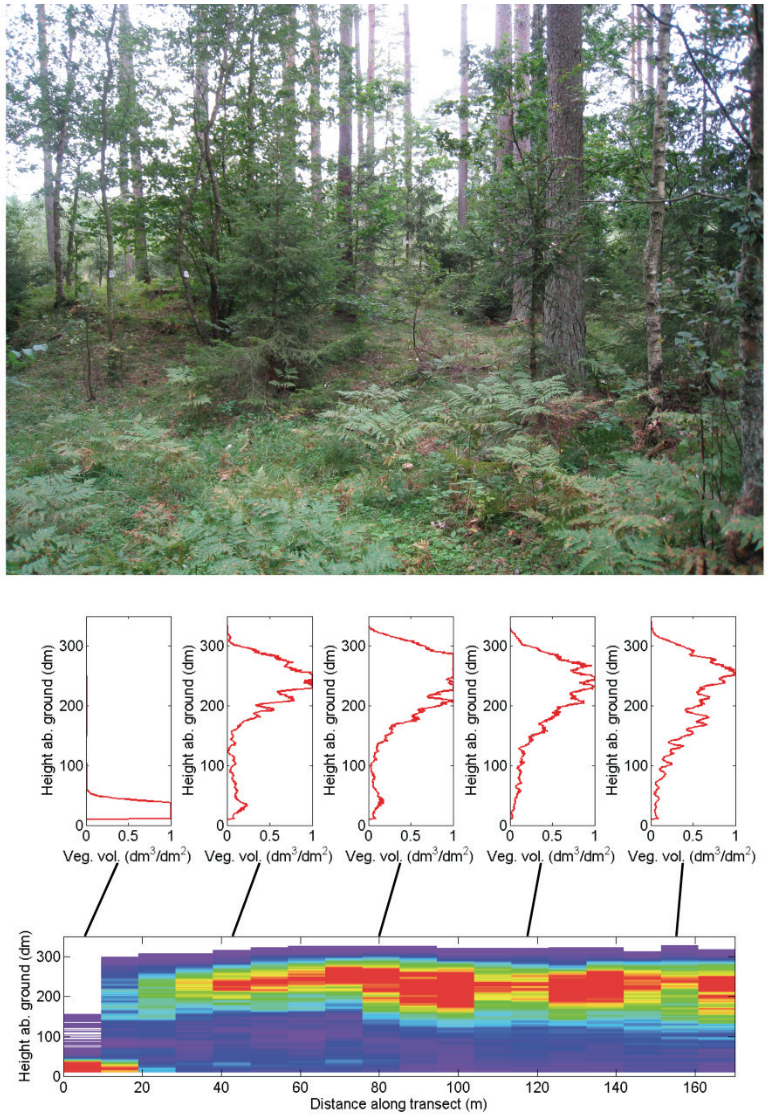

Figure 8. Example of a photograph from a pine-dominated field plot with understory (top), vegetation volume profiles (middle), and a transect of vegetation volume from the same area (bottom; colour scale, blue indicates low values and red indicates high values). The field plot and the second vegetation volume profile from the left are at approximately the same location.

5 Discussion

5.1 Individual tree crown delineation

The fraction of field-measured trees that were linked to tree crowns delineated from ALS data was larger for trees with a larger DBH. This was the case for tree crowns delineated from surface models as well as tree crowns delineated in three dimensions with the model-based clustering approach. The delineation identified larger trees, especially in the dominant tree layer, which is consistent with earlier studies (Persson *et al.*, 2002). More trees with a smaller DBH (<20 cm) were linked to tree crowns delineated with the model-based clustering approach than to tree crowns delineated from a surface model, especially in field plots with higher mean tree height. This suggests that the model-based clustering approach is more successful at identifying trees in the understory below the dominant tree layer. However, the model-based clustering approach resulted in more erroneously delineated tree crowns that were not linked to any field-measured tree. Those un-linked clusters may correspond to parts of larger trees or to trees with a DBH smaller than the criterion to measure a tree in the field. This is also consistent with earlier studies (Reitberger *et al.*, 2009). This means that some of the delineated tree crowns that were linked to smaller field-measured trees could be erroneously delineated tree crowns.

The CS model was based on *a priori* knowledge about the shape of tree crowns. Earlier studies have shown that this approach is successful for delineation of tree crowns under various forest conditions and may result in equal or higher accuracy than k-means clustering in three dimensions (Vauhkonen *et al.*, 2011). Three-dimensional delineation of tree crowns could also benefit from using *a priori* knowledge about the tree crowns. In paper II, this was achieved by fitting a parabolic surface to the top of each cluster and by joining clusters that were close enough along a vertical axis. This was a new approach compared to earlier 3D analysis of individual tree crowns (e.g., Barilotti *et al.*, 2008; Wang *et al.*, 2008; Reitberger *et al.*, 2009; Gupta *et al.*, 2010).

Even when statistical methods are used to estimate lists of trees based on the properties of the delineated tree crowns, individual tree methods generally underestimate the number of trees. One reason is that tree crowns cannot be delineated if they contain too few ALS returns. This applies in particular to smaller trees. Additionally, only part of the laser light can pass through the higher layers of the canopy, which means that the measurements will not cover the area completely (e.g., Harding, 2009). Due to this occlusion effect, especially trees below the dominant tree layer will give rise to very few of no ALS returns. Hence, usually only a subset of tree crowns may be delineated from ALS data and it is difficult to estimate the complete tree size distributions.

5.2 Estimation of tree lists from individual tree methods

In this thesis, three different statistical approaches were used to estimate lists of trees from individual tree crowns delineated from ALS data (i.e., not just the trees that can be identified by detecting local maxima in ALS data): *i*. Estimation of the number of trees and forest variables per tree crown using a classification approach and regression respectively (paper I). *ii*. Adjustment of the tree lists derived from delineated tree crowns with target distributions of tree heights and DBH at plot level and rescaling with the plot-wise volume estimates (paper I). *iii*. Imputation of trees to the delineated tree crowns using k-MSN (paper II). All approaches resulted in a smaller RMSE and bias at plot level than estimation of one tree per delineated tree crown.

In paper I, estimation of one tree per segment resulted in an underestimation of stem density and stem volume. The classification and regression approach reduced the error. In another study, probability models have been used to estimate the number of trees associated with each delineated tree crown with features extracted from the crown areas as independent variables (Flewelling, 2008). The models resulted in unbiased estimates at stand level even though the fraction of linked tree crown segments was only 48% of the total number of trees and 74% of total basal area. However, a separate model was needed to handle unseen trees (i.e., trees that had not been linked to any of the delineated tree crowns).

In paper I, adjustment using the tree size distributions and stem volume in the field plots reduced the bias even further. The accuracy of the stem volume estimated from adjusted tree lists was similar to direct regression estimates at plot level. The study area in paper I is situated in boreal forest near the tree line and has a high fraction of deciduous and mixed forest. Furthermore, the radii of the field plots were only 6 and 8 m. Hence, estimation of forest variables from ALS data is more difficult for this study area than for coniferous-dominated forest and using field plots with larger radii, especially estimation of tree size distributions.

Finally, the k-MSN approach in paper II resulted in a high accuracy at plot level, which is consistent with previous studies (Breidenbach *et al.*, 2010a; Holmgren *et al.*, 2010). k-MSN imputation of stem properties from harvester data based on the ALS data in each segment has been used to estimate tree lists (Holmgren *et al.*, 2010). For estimation of several correlated variables, it is difficult to fit parametric models. Breidenbach *et al.* (2010a) used a similar imputation approach that they named semi-ITC to estimate the properties of the trees contained in each segment. The results were more accurate than estimates from regression models at area level.

The model-based clustering resulted in a large number of small clusters that were not linked to any field-measured trees. However, the properties of the un-linked clusters differed from the linked clusters. Hence, the result of the imputation was not impaired by the un-linked clusters. The accuracy was similar to the imputation of segments. Three-dimensional analysis of individual trees might have more advantages in multi-layered forests than in managed boreal forests where statistical analysis of tree crown segments delineated from a surface model provides high accuracy and small bias.

5.3 Canopy structure

Paper IV presented new methods for estimation of vegetation volume profiles from waveform ALS data as well as discrete return ALS data. The methods were based on a model where the Beer-Lambert law was used to describe the total vegetation volume measured in field as a function of the penetration ratio (i.e., the fraction of laser light reaching the ground) derived from ALS data. Exact measurements of LAD are extremely laborious. However, the vegetation volume profile is probably highly correlated with LAD, which means that the total vegetation volume is correlated with LAI. LAI has previously been estimated from ALS data with models based on the Beer-Lambert law and penetration ratio (Solberg *et al.*, 2009).

Additionally, paper IV presented a new algorithm to normalize the intensity values of the received ALS waveforms based on the intensity that is reflected from higher layers of vegetation. The normalization was also based on the Beer-Lambert law. This approach has not been used for modelling of ALS data from terrestrial vegetation before, but it is was inspired by bathymetric laser scanning, where the light pulse in the water is attenuated exponentially based on water clarity (Guenther *et al.*, 2000). The normalization algorithm was a simplification and approximation. The diameter of the laser footprint at ground level is typically a few dm and most of the surfaces within a footprint are not spread along the beam. Hence, it might be more appropriate to first aggregate waveforms over a slightly larger area, for example, one square meter, and then apply a normalization algorithm to the aggregated waveforms. If calibration data are available, the backscatter cross-section for each component of the waveform can be derived (Wagner *et al.*, 2008). The cross-section of the first reflecting surface can be derived directly from the amplitude and width of the corresponding component. The cross-sections of subsequent components can be calculated by observing that the total area of the reflecting surfaces should be equal to the footprint (Wagner *et al.*, 2008).

The results indicate that estimation of vegetation volume profiles is feasible and may be used for creation of 3D vegetation models for large areas. Even though the differences between the methods were small, they suggest that waveform ALS data describe the vegetation structure more accurately than discrete return ALS data and that processing of the waveforms may improve the result.

The methods require field measurements of the total vegetation volume from a number of field plots as training data for rescaling of the ALS profiles. However, field-measurements of the vegetation volume profiles are not needed. Before rescaling, the ALS profiles represent the relative amount of vegetation material at different heights above the ground, although the ALS profiles cannot be compared for different field plots since the distance to the scanner varies, which means that the intensity value varies accordingly. Additionally, the laser scanning system used in paper IV did not provide information about the sensor gain. A possible use of the ALS profiles without rescaling would be for manual interpretation.

5.4 Area-based methods versus individual tree methods

Individual tree methods provide information about most trees in the dominant tree-layer, but smaller trees below the dominant tree layer often cannot be delineated. The estimates from area-based methods have low bias, which makes it possible to calibrate the estimated DBH and tree height distributions to better describe the field-measured distributions (Maltamo *et al.*, 2007). However, small field plots contain too few trees for estimation of distributions. In that case, individual tree methods may better describe the tree size distribution in the field plots. A mixture of tree species within the field plots is also a motivation for individual tree methods since tree species classification may be done of the delineated tree crowns (Brandtberg *et al.*, 2003; Holmgren & Persson, 2004; Vauhkonen *et al.*, 2008).

Most currently used area-based methods only consider the vertical distribution of the ALS data. Individual tree methods generally operate in 3D or 2.5D (i.e., surface models), which means that more information is extracted from the ALS data. Information from individual tree methods can be utilized in area-based approaches. This may be done, for example, by using the distribution of heights from delineated tree crowns as independent variables for estimation of tree size distributions (Holmgren & Wallerman, 2006) or by deriving stem attributes based on delineated tree crowns and regional allometric functions, aggregating the stem attributes to plot level, and using the aggregated values as training data for an area-based method (Vastaranta *et al.*, 2012) or as independent variables for an area-based method (Hyyppä *et al.*, 2012). Information about the number of trees in different height classes could also be valuable for describing the vertical vegetation structure.

Imputation of trees based on features extracted from delineated tree crowns may be seen as a combination of individual tree methods and area-based methods, utilizing more details than if the ALS data are aggregated to plot level. This is consistent with such approaches having resulted in a higher accuracy than regression estimates at plot level (Breidenbach *et al.*, 2010a). In paper II, imputation was done based on tree crowns delineated in 3D with model-based clustering, which was a new approach.

5.5 Combination of airborne and terrestrial laser scanning

Paper III presented a new method to combine TLS and ALS data at the individual tree level for estimation of DBH, stem volume, and tree height. Tree stems found from TLS data were used as training data for tree crown segments from ALS data. The training data included only the subset of trees for which the accuracy of the stem diameter estimated from TLS data was likely to be high (i.e., the method did not require TLS estimates for all trees). The accuracy of the estimates from ALS data when using TLS data as training data was almost as high as when using manual field inventory as training data. The method could reduce the need for manual field measurements, which means that the field inventory could be done more efficiently and with a smaller risk for human errors.

Canopy structure could also be estimated using a combination of TLS and ALS data. Vegetation volume profiles derived from field data have considerable uncertainty and using TLS data is a possibility to obtain more accurate measurements of the canopy structure. Detailed models of the tree stems, foliage, and branches may be created from TLS data at tree level (Pfeifer & Winterhalder, 2004; Cote *et al.*, 2009) or at plot level (Henning & Radtke, 2006b; Van der Zande, 2008; Van der Zande *et al.*, 2011). Canopy structure has been studied using a combination of TLS and ALS data (Lovell *et al.*, 2003; Hilker *et al.*, 2010; Hosoi *et al.*, 2010; Jung *et al.*, 2011) but more research is needed to make use of the full potential to model tree stems, foliage, and branches.

5.6 Estimation of stem diameters from terrestrial laser scanning

The errors of the DBH estimated from TLS data were partly due to other trees and foliage obscuring the measurements of the tree stems. The RMSE of the estimated DBH was larger for spruce trees than for pine trees, which is consistent with spruce trees having denser branches. Noise reduction is essential to select the laser reflections exclusively from the tree stems. For this purpose, methods from image analysis and digital photogrammetry are useful, although domain specific methods are required to take the obscuring effect of foliage into account (Pfeifer & Winterhalder, 2004; Cheng *et al.*, 2007).

The success of the estimation of stem diameters is dependent on that laser reflections are captured from a large enough part of the tree stem. This means vertically along the part of the stem that should be estimated and from a large enough horizontal section of the stem. If the tree stem is obscured by other trees or foliage, the accuracy of the estimated stem diameter will be lower. One solution to this is to collect TLS data at multiple positions. However, in that case, criteria are also needed to verify that laser reflections are captured from a large enough part of the stem. To achieve this it is useful to estimate the accuracy of the estimated DBH directly from the laser reflections. If the accuracy is lower than requested, additional data may be collected at another position. If the estimates are used as training data for remotely sensed data, it may be feasible to select the tree stems where the accuracy is likely to be high.

5.7 Conclusions

The main findings in this thesis are summarized in the following bullet points.

- Delineation of tree crowns from a surface model based on *a priori* knowledge about the shape and proportion of the tree crowns identifies most of the trees in the dominant tree layer of coniferous-dominated boreal forest and has been shown to perform at least as well as some 3D methods. Three-dimensional methods may also benefit from using *a priori* knowledge about the tree crowns.
- Delineation of individual tree crowns from ALS data often fails to identify trees standing close together and trees below the dominant tree layer. To derive lists of individual trees, the delineated tree crowns can be linked to field-measured trees, and models can be created to estimate a number of trees with associated stem attributes for each delineated tree crown. The accuracy of such statistical analysis when aggregated to plot or stand level is comparable to the accuracy of area-based methods.
- The accuracy of tree lists derived with statistical approaches from delineation of surface models was similar to the accuracy of tree lists derived with statistical approaches from 3D methods when aggregated to plot level.
- TLS provides a possibility to find tree positions and estimate stem diameters automatically. If the stems will be used as training data for individual tree methods, the tree positions must be co-registered, in which case the error of GPS measurements below a canopy as well as the obscured sectors in the TLS data must be taken into account.
- Furthermore, if the stems found from TLS data will be used as training data for individual tree methods, it may be possible to use only a subset of trees where the accuracy of the estimates from the TLS data is likely to be high. The accuracy may be estimated directly from the laser reflections together with properties of the estimated stems.
- Characterization of canopy structure is possible from ALS data using statistical models trained with field measurements of total vegetation volume. The accuracy using waveform ALS data is slightly higher than when using discrete return ALS data.
- One limitation for analysis of canopy structure is that the field measurements are laborious but simplified measurements introduce errors. This could be improved by using TLS to measure the canopy structure.

5.8 Future work

The model-based clustering was a first attempt to develop an algorithm for delineation of tree crowns from ALS data in three dimensions using *a priori* knowledge about the shape and proportion of the tree crowns. The parameters of the model were selected subjectively. One way to improve the modelling would be to run the algorithm with different combinations of parameter values and select the combination resulting in the most accurate delineation, meaning that a large fraction of field-measured trees would be linked to delineated tree crowns (i.e., small omission error) and a large fraction of the delineated tree crown would be linked to field-measured trees (i.e., small commission error). Additionally, the principles of the model-based clustering could be improved by introducing other distance measures to better model the shape and density of tree crowns.

The model-based clustering was validated in a predominantly managed boreal forest. Compared to delineation of a surface model, the model-based clustering identified a larger fraction of small trees below the dominant tree layer. To make use of this, the model-based clustering should be validated in a multi-layered forest. The measurement density of the ALS data should be high to make sure that enough measurements originate from lower vegetation layers. Waveform ALS data could be useful for obtaining more information about lower layers.

Since the model-based clustering delineates the whole tree crown and not just the top of the tree crown, classification of tree species could be improved compared to delineation of tree crowns from surface models. This is especially so for multi-layered forests where the tree crowns in the dominant tree layers could potentially be separated from the understory. Also for this purpose, waveform ALS data could be useful in order to base the tree species classification on the echo width and other variables derived from the waveforms.

The methods for estimation of vegetation structure could be used to create raster maps describing the vegetation density in different height layers for large areas. This information could be analyzed together with data on the occurrence of different species (i.e., plants as well as animals). The vegetation structure could also be used as input to habitat models, where properties of the whole landscape are combined to predict the chances for occurrence of species in the landscape.

ALS and TLS data have previously been combined for estimation of canopy structure. This has been based on the density of ALS returns and TLS reflections in voxels. Another approach would be to delineate tree crowns from the ALS and TLS data based on *a priori* knowledge of the shape and proportion of tree crowns. Such model-based analysis could improve the estimation of the vegetation structure since information could be derived even for tree crowns containing only a few ALS returns or TLS reflections. However, care must be taken to create appropriate models that can represent all frequently occurring natural shapes and proportions.

The stem form and the positions of branches can be derived from TLS data. Such detailed analysis is not possible from ALS data, but line features representing the stems and branches can be derived from ALS data, for example, using a combination of k-means clustering and principle component analysis (Ko *et al.*, 2010). This information could be combined with detailed information about the stems and branches derived from TLS data.

The normalization algorithm used to compensate the waveform intensity values for the shielding effect of higher vegetation layers on reflections from lower layers was a simplification and approximation. It has only been validated by comparison of the results from estimation of canopy structure in paper IV. The algorithm should be validated using simulations of scattering of laser light and compared with radiative transfer models. If the results from the simulations are promising, the algorithm should be validated further in an experimental setting with laser measurements of tree crown models with known reflectance properties and real tree crowns with known geometry.

The wavelength of the currently used airborne laser scanners for terrestrial mapping is usually 1064 nm, which is in the near-infrared spectrum. The laser scanning systems are constructed to measure the topography, but the wavelength is still useful for vegetation measurements. To improve analysis of the vegetation, laser scanners with other wavelengths could be introduced. This has been done in experimental systems (Wallace *et al.*, 2012). To make best use of the data, laser scanners with different wavelengths could be validated in an experimental setting with tree crown models with known reflectance properties and real tree crowns with known geometry.

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