A proposed decision support tool for wood procurement planning
based on stereo-matching of aerial images

Johan Viklund

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Handledare:
Jörgen Wallerman

Sveriges lantbruksuniversitet
Institutionen för skoglig resurshushållning
901 83 UMEÅ
www.slu.se/srh
Tfn: 090-786 81 00

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Master of Science in Forestry (SLU, Sweden),
Ex 0768
Supervisor: Jörgen Wallerman, SLU, Dept. of forest resource management, Remote sensing
Examiner: Johan Fransson, SLU, Dept. of forest resource management, Remote sensing
External supervisors: Håkan Johansson SCA Skog AB, Kristoffer Önneholm, SCA Skog AB & Magnus Jutterström, Metria AB.

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Abstract

In Sweden the cap portion of the harvested stem volume derives from Non-Industrial Private Forest (NIPF) owners. In the current study a Decision Support Tool (DST) for wood procurement planning based on stereo-matching of aerial images is presented. Two stages are described, namely (1) automatic segmentation using a Mean Shift algorithm; (2) wall-to-wall mapping of the stands using Semi-Global Matching (SGM) in combination with a high-resolution Digital Elevation Model (DEM). The study was conducted in a coniferous boreal forest area in northern Sweden. 365 sample plots (8 m radius) were measured in the field where *HGV (dm)* ranged between 49.0 - 246.0 dm (mean 139.3 dm), *DGV* 67.0 - 400.0 mm (mean 196.8 mm), *VOL* 7.0 - 665.0 m^3/ha (mean 151.1 m^3/ha) and *BA* 20.0 - 635.0 dm^2/ha (mean 204.9 dm^2/ha). Point clouds were extracted from the aerial images with 60% forward overlap. A canopy cover metric was used to improve the *VOL* and *BA* estimations. Plot level accuracies were calculated using leave-one-stand-out-cross-validation resulting in a Root Mean Square Error (in percent of surveyed mean) for: *HGV* 11.2%, *DGV* 15.2%, *VOL* (m^3/ha) 33.5% and *BA* 30.3%. Each stand was given an average of the estimated forest variables enabling ranking between the stands based on their estimated values. The results indicated that the proposed DST can be used as a support in wood procurement planning. Aerial images are an appropriate data source in the proposed DST, mainly because of the readily availability and low cost.

Keywords: Semi-global matching, canopy cover, forest inventory, plot level forest variables, stem volume.

Preface

This study is a MSc thesis in Forestry at the Department of Forest Resource Management, Swedish University of Agricultural Sciences (SLU), Umeå, Sweden. The thesis covers 30 ECTS, advanced level (A2E) and is part of the Master of Science in Forestry program. The study is supported by the companies Svenska Cellulosa Aktiebolaget Skog AB (SCA Skog AB) and Metria AB. This master's thesis would not be the same without the contribution of the following people, to whom I am in debt, without any mutual order: Magnus Jutterström, Metria AB, for providing aerial images and through his actions encouraged the work; the result would not have been as good without his help. Kristoffer Önneholm and Håkan Johansson, SCA Skog AB, for providing field data and inexorably answered my questions. I extend great recognition to Fanny Viklund for her tireless revision of the language. I am also very grateful to my supervisor Dr. Jörgen Wallerman for his constructive feedback and continuous guidance throughout the entire research process.
I finally wish to thank the teachers and researchers from the Section of Forest Remote Sensing at SLU for their kind responses and discussions whenever a question was raised. To the many of you who have contributed, let me reiterate my gratitude and my appreciation.

Umeå, March 2014

Johan Viklund

Introduction

Background

In order to make the correct silvicultural decisions, good information about the forest condition is required (Duvemo & Lämås, 2007). In Sweden, the last nationwide survey at stand level was initiated and carried out by the Forest Agency between the years 1982-1993 (Wijk, 1998). The survey was designed to provide a good description of forestry potential, to raise silvicultural activity in individually owned forests and to be used as a tool for governmental provision and support. As of today, the information from this survey is about 25 years old and it has not been updated since the survey was completed. In recent years, progress in forest remote sensing has generated new possibilities to extract forest information in a more accurate and rational way.

The Swedish productive forest land is divided into different ownership classes where Non-Industrial Private Forest (NIPF) owners form the largest group, owning 50% of the forest land (Forest Agency, 2013). Harvesting statistics from 2010-2012 shows that 59.6% of the annual gross harvesting (m^3) was derived from NIPF owners. In other words, the cap portion of the harvested volume comes from NIPF owners.

As a consequence of the proportion of harvested volume originating from NIPF owners, procurement planning targeting NIPF owners is a key part of the Swedish forest industry. In a Swedish Government Official Report from 1981 the issue of low harvesting activity on individually owned forests was addressed. The low activity was said to cause large socio-economic losses (SOU 1981:81). In order for the forest owner to have an influence on their forest management activities, a forest management plan is a good planning instrument (Ingemarson et al. 2004). A forest management plan is a simple and efficient tool for the NIPF owners to control and achieve long-term sustainable forest management that benefits both the NIPF owners and the society at large (SOU 2007/08:108). However, there is no obligation for NIPF owners to establish a forest management plan (SFS 2010:956). Therefore, it is up to the NIPF owner to obtain adequate information about the forest property and the associated silvicultural decisions. Studies have shown that there is a strong correlation between per-hectare timber inventory and timber harvesting (Brännlund, 1988; Kuuluvainen, 1989). A NIPF owner with a forest management plan or corresponding information is thus more prone to harvesting. Forest companies often purchase the right to harvest timber on NIPF owners' forest properties. Thus, this indicates that there might be a shared interest between forest companies and NIPF owners to update forest information.

In general, forest management plans in Sweden are mostly made by contractors (Lönnstedt, 1997). Unlike the nationwide forest inventory performed by the Forest Agency, the information from the forest management plans is usually not available to the procurement organizations within the forest companies. Consequently, it is reasonable to assume that procurement organizations within forest companies are interested in information corresponding to forest management plans, for example a decision support tool based on forest remote sensing.

Forest remote sensing

In many Nordic countries, including Sweden, the traditional method for describing forest characteristics is by stand level field inventories. The stands are first manually delineated using aerial photographs viewed in stereo and later subjectively inventoried (Åge, 1983). This method typically provides estimates with Root Mean Square Error (RMSE) on stand level of 15-25% for stem volume and 10% for tree height (Ståhl, 1992). This procedure is both subjective and labor intensive, and therefore costly (Holopainen & Talvitie, 2006).

In an effort to reduce costs and achieve more accurate forest data, research in forest remote sensing has been an active topic in Nordic countries (Maltamo et al. 2011; Næsset et al. 2004; Holmgren, 2004). According to Lillesand et al. (2004) remote sensing may be described as the discipline that deals with obtaining information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation. The goal of forest remote sensing is to add value to the planning process and to the outcomes of forestry (Ståhl et al. 1994). Information retrieved from forest remote sensing should contain more accurate information at the same cost or, preferably, less cost compared to available manual methods (Holmgren & Thuresson, 1998).

During the last decade Airborne Laser Scanning (ALS) has revolutionized the methodology of forest inventories (Means et al. 2000; Næsset, 2002). The Nordic countries and particularly Finland and Norway gradually shifts from subjective inventory methods towards forest variables estimates with ALS (Maltamo et al. 2011). Several European countries, including Sweden, have initiated a nationwide ALS campaign with the purpose to map the entire country and create a new Digital Elevation Model (DEM). A DEM describes the height of the land surface over a reference surface, typically the geoid. In Sweden, this is performed by the Swedish National Land Survey (Lantmäteriet). Although the current situation provides stakeholders with high quality 3D information from the national ALS campaign, there is no plan for a new campaign (Lysell, 2012). However, Lantmäteriet performs regular aerial photo missions with a continuous photo interval described in a long-term plan for aerial digital photographs. In the long-term plan, the south of Sweden and the north-eastern coastal areas are covered every second year and inland areas of northern Sweden every 4-6 years (Lantmäteriet, 2013a). This means that images from the regular aerial photo missions provide nationwide data with higher temporal resolution compared to ALS. The recent technological advances in high-resolution acquisition of digital stereo images, combined with automatic image-matching methods together with an existing high resolution DEM creates new possibilities to acquire 3D information. This combination of technologies enables automatic measurements in 3D instead of assessments of tree height by manual interpretation of aerial images in stereo. Since large areas can be measured automatically with the new technology, studies have shown that image matching can be a used as a cost-effective approach for estimation of forest variables (Järnstedt et al. 2012; Straub et al. 2013; Nurminen et al. 2013) (Table 1).

Table 1. Overview of previously published research using both image matching and ALS. *HGV* (basal area weighted mean height), *DGV* (mean diameter, basal area weighted), *VOL* (volume) and *BA* (basal area). Forward stereo overlap in percent. All per-reviewed articles used a plot-wise validation.

Study	Location	Sensor	Plot variable	Plot size (m^2)	Number of plots	RMSE (%)
(Järnstedt et al. 2012)	Southern Finland	UltraCamXp (70%), GSD (0.25 m)	Mean tree height	300	402	28.2
			Mean diameter			33.7
			VOL			40.4
			BA			36.2
(Straub et al. 2013)	Southern Germany (mixed forest)	UltraCamX (65%), GSD (0.20 m)	VOL	500	228	37.9
			BA			35.3
(Nurminen et al. 2013)	Central Finland	UltraCamD (60%), GSD (0.15 m)	HGV	392*	89	7.6
			Mean diameter			12.2
			VOL			22.8
(Holmgren, 2003)	Southern Sweden	ALS	HGV	314	65	11
			VOL			22
(Næsset, 2004)	Southeast Norway	ALS	DGV	233	100	13.5–20.0
			BA			14.8–22.5

*Varying plot size where the area weighted mean is presented

Aerial images

A digital camera captures the solar radiation reflected by objects visible from the camera's point of view (Honkavaara et al. 2009). If one object (e.g., a tree) is visible in two images, the same object is located in different parts of the images due to the movement of the airplane and the different viewing angles. Consequently, protruding objects are displaced radially from the image center. This displacement is called parallax and allows for stereo vision and triangulation, i.e., height measurement (Boberg, 2006). In order to measure the parallax, and ultimately convert 2D images to 3D structures, the same object has to be identified in both images. There are several algorithms available for image matching: cross-correlation and least squares (Ackermann, 1984), feature-based methods (Lowe, 2004) and Semi-Global Matching (SGM) (Hirschmüller, 2005 & 2008). If height measurements are calculated evenly in the overlapping images, a Digital Surface Model (DSM) can be created. In contrast to the DEM, the DSM's height values correspond to the height of the earth's surface, including objects on it, e.g., trees. In a study performed by Gehrke et al. (2010) a DSM derived from aerial images matched using a SGM algorithm was compared to a DSM from ALS data. Gehrke et al. (2010) concluded that a DSM from aerial images can be an effective alternative to a DSM derived from ALS. This indicates that objects visible in stereo images can be measured with equal accuracy as ALS. In the available peer reviewed articles where aerial images have been used to estimate forest variables, Bohlin et al. (2012) utilized a feature-based method, Straub et al. (2013), Järnstedt et al. (2012) and Nurminen et al. (2013) used a cross-correlation method.
Both Nurminen et al. (2013) and Straub et al. (2013) pointed out the lack of studies where SGM is utilized for image matching and forest variable estimates using aerial images. Therefore, an implementaion of the SGM algorithm provided in the software package SURE (Rothermel et al. 2012) was used in the current study.

Lantmäteriet offers a readily available source of aerial images with a higher temporal resolution compared to ALS. Due to the price fluctuation it is difficult to determine the exact cost of deriving forest information using different sensors. Even so, the cost of aerial images is at least half compared to ALS (White et al. 2013a). Although ALS has demonstrated great potential in forest variable estimates, the continuity of ALS is believed to be substandard (Lysell, 2012). Important factors in the choice of data in applications mapping large geographic extents are high temporal resolution, a proven ability to successfully estimate forest variables, and finally, lower acquisition cost compared to available alternatives. Aerial images are an attractive source since they meet the stated requirements. This is especially evident in Sweden, since Lantmäteriet distributes the aerial images at a marginal cost and since aerial images are already implemented in the current inventory methodology (Åge, 1983).

Forest variable estimation

There are mainly two methods to create statistical relationships between data from forest remote sensing and ground plots: parametric and non-parametric approaches. In forest variable estimations using ALS data, parametric methods have been successfully used by, e.g., Means et al. (2000), Næsset (2002) and Holmgren (2004). Later on, point clouds derived from image matching have been successfully used by, e.g., Bohlin et al. (2012) and Straub et al. (2013). Non-parametric approaches have been implemented in an ALS context by, e.g., Packalén and Maltamo (2007) and Hudak et al. (2008) and later on by Nurminen et al. (2013) using image matched point clouds. In a study by Næsset et al. (2005) an evaluation between Ordinary Least Squares regression (OLS), seemingly unrelated regression, and partial-least squares regression showed that no model is superior to the others. This result leads to the recommendation to use OLS due to the model performance and model simplicity. Based on previous results (Bohlin et al. 2012; Straub et al. 2013) and the conclusion from Næsset et al. (2005), a parametric regression model (OLS) was used in the current study. An additional advantage with OLS is the simplicity to implement the models in a wall-to-wall estimation using common GIS-applications, which also suits the purpose of the current study.

Decision support tool

As forest management evolves new demands for tools which facilitate planning and decision making arises. Decision and planning can be supported in various ways and with various degrees of sophisticated systems. These systems are generally divided into two classes; Decision Support Systems (DSSs) and Decision Support Tools (DSTs) (Vacik & Lexer, 2013). In brief, a DSS/DST helps decision makers in semi-structured problems where human judgment is vital for problem solving (McNurlin & Sprague, 2004; Martinsons & Davison, 2007). The difference between DSS and DST is that a DST can be anything from a flowchart on a paper to advanced simulation models, while a DSS has a clearer framework for which components that should be included (Vacik & Lexer, 2013; Stair & Reynolds, 2005).

In the current study, a DST was proposed in order to identify potential harvesting within a defined area regardless of the ownership category. The DST was based on digital aerial images. The images were matched using an SGM-algorithm which converts aerial images from 2D to 3D. Forest variables were then estimated in a similar manner as in ALS-based forest inventory. The result was a wall-to-wall estimation of forest variables in a predefined area. However, in order for a DST to help the decision maker it has to be easy to use and easy to implement (Vacik & Lexer, 2013). Since stands are considered the smallest descriptive unit in the Swedish forestry it is important that a DST copes with these prevailing conditions. As of today, stands are manually segmented into homogenous areas with regard to height, stem volume, tree species and forest management (Mustonen et al. 2008). The stand size is usually between
2 - 5 ha (Holopainen & Talvitie, 2006). In the proposed DST an automatic segmentation was performed. Because of the segmentation and the forest variable estimates, the information output from the DST is similar to a forest management plan and can therefore assist both NIPF owners and the procurement organizations in forest management decisions. In addition to the objective data that can be obtained from the DST, adjacent stands with harvesting potential can also be identified. These identified adjacent stands can potentially be harvested sequentially and concentrations savings can be obtained. The concentration savings are related to the cost of building roads and moving harvest equipment (Gustavsson et al. 2000; Baskent & Jordan, 1991).

Objective

The objective of the current study was to develop a DST, which aims to simplify wood procurement planning and forest management by using stereo-matching of aerial images and thereby estimate forest variables. The DST output intends to visualize harvesting potential within a given area.

Material

Study area

The study area is located at approximately 64°50’ N, 20°00’ E in the north-eastern part of Sweden in the counties of Norrbotten and Västerbotten. It spans between latitude 63.2° N and 65.5° N, and elevation ranges from 29 m to 350 m above sea level (Figure 1). According to the surveyed plots, the essential tree species distribution of the study area is: Scots Pine (*Pinus sylvestris* L.) 49%, Norway Spruce (*Picea abies* L.) 37%, Birch (*Betula* spp.) 9% and Lodgepole pine (*Pinus contorta*) and other deciduous 5%. According to official Swedish statistics the tree species distribution in the plots is representative to the distribution in the study area (Forest Agency, 2013).

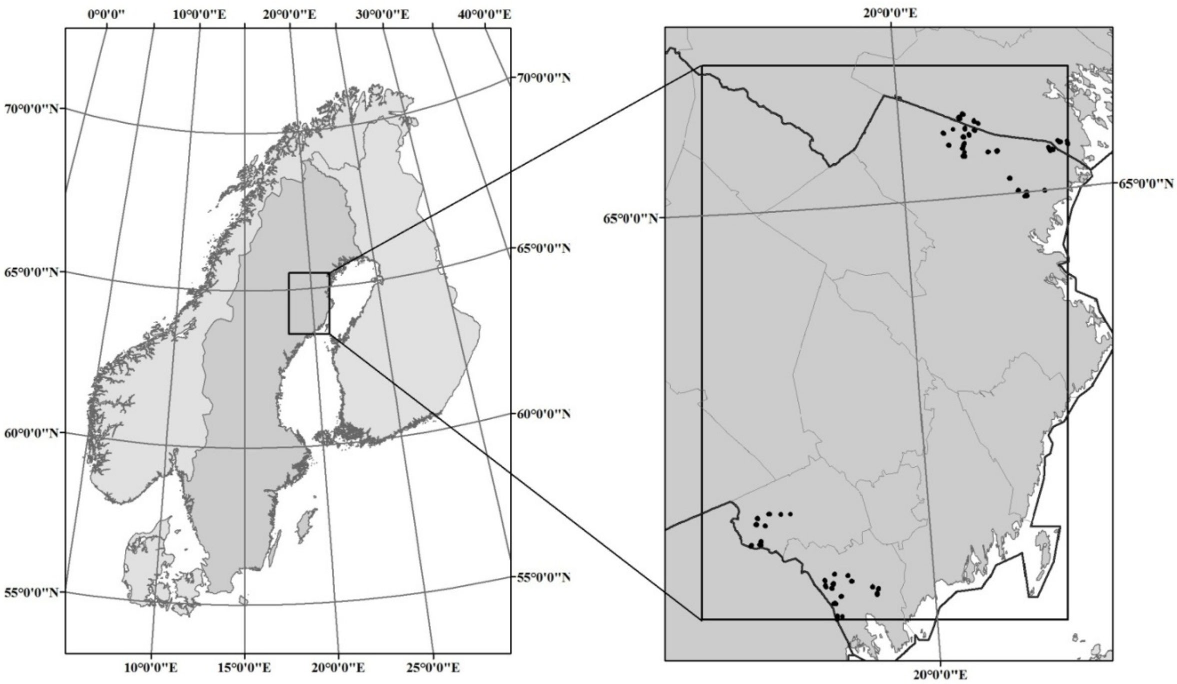


Figure 1. Location of the study area (left) and the sample plot layout with municipality and county borders (right).

Inventory data

All the plots used in the current study are located within the forest holdings of SCA Skog AB (SCA). They were obtained by SCA and their inventory personnel who provided a total of 366 plots from 66 stands. The main purpose of the inventory was to serve as a foundation for the company's strategic plan and associated harvest calculations.
The current study uses data provided by this inventory.

SCA's inventory was carried out according to the Forest Management Planning Package (Jonsson et al. 1993) during the growing season of year 2012. Data from SCA's stand register was utilized for stratification into four strata based on different management classes (Table 2). Thus, by using strata, SCA ensured that all forest types were represented in the sample. In the stratification, stands with higher stem volume and accordingly imminent harvesting had a greater probability to be included.

Table 2. The four strata

	Stratum (1-4)
1.	Production forest
2.	Stands dominated by Lodgepole pine (*Pinus contorta*)
3.	Voluntary provisions for environmental protection
4.	Other management classes*

* The stratum "Other management classes" refers to stands with deviant management praxis, for example selective cutting or management for deciduous dominance.

All field plots were circular, had 8 m radii and were objectively inventoried. All trees with a Diameter at Breast Height (*DBH*) greater than 4 cm were calipered. If the *DBH* was less than 4 cm, but the tree was expected to be merchantable timber in a future harvesting it was also included in the inventory. For the data collection a hand held device (TDS Ranger) with a forest management software package was used. A digital caliper (Mantax Digitech) was connected to the TDS Ranger and automatically registered the measured diameter. For all height measurements a Vertex IV hypsometer from Haglöfs was used. At each plot were: sum of Basal Areas (*BA*) per hectare, basal area weighted mean height (*HGV*), basal area weighted mean diameter (*DGV*) and mean stem volume per hectare (*VOL*) measured. Stem volume estimation of the sampled trees was based on volume functions for individual trees (Brandel, 1990) and calculated as the total stem volume (m^3) of the trees (inculding top and bark).

The GPS centroid of the plots was determined by a handheld mapping device (Ashtech MM 100) and position data were logged during 15 minutes at each plot for later post processing. The software MobileOffice 2.1 was used for the differential post-processing correction procedures. MobileOffice 2.1 uses permanent base stations (SWEPOS) to maximize plot positional accuracy, which results in a sub meter GPS-accuracy (Johansson, 2013, pers. comm.). One plot was excluded from the sample due to its large influence on the *DGV* estimation, leaving a total of 365 plots (Table 3).

Table 3. A summary of 365 field plots derived from 66 stands

	N	**Min**	**Mean**	**Max**	**STD**
HGV (dm)	365	49.0	139.3	246.0	41.3
DGV (mm)	365	67.0	196.8	400.0	64.3
VOL (m^3/ha)	365	7.0	151.1	665.0	104.9
BA (dm^2/ha)	365	20.0	204.9	635.0	104.9

Remote sensing data

Airborne laser scanner data

The ALS data in the current study were provided by Lantmäteriet's ALS project.
The purpose of the project is to create a DEM of Sweden (Lysell, 2012). The ALS data collection is still an ongoing campaign and as a consequence the ALS data used in the current study originates from either 2009 or 2011.

All plots were scanned during leaf-on season using an airplane mounted laser scanner. The ALS data collected in 2009 were scanned with a Leica ALS 60, while ALS data captured in 2011 were scanned with a Leica ALS50-II/69. Both laser scanners were operated at a flight altitude of 1700 - 2300 m above ground level with a scanning angle of 20° and a swath overlap of 20%, giving a footprint on the ground of 0.5 - 0.7 m. The point density was in the interval between 0.5 - 1 points/m^2 (Lantmäteriet, 2012).

Before the ALS data were provided to the current study, Lantmäteriet preprocessed the data. Laser returns were classified as ground and non-ground returns using a progressive triangular irregular network densification method (Axelsson, 1999) in TerraScan software (Soininen, 2010).

Aerial images

Lantmäteriet provided 234 aerial images covering the study area. All images were acquired with a large format camera: Intergraph Z/I Imaging Digital Mapping Camera (DMC) (Hinz et al. 2001) (Table 4).

Table 4. Z/I DMC specifications

Panchromatic camera heads	4
Multispectral camera heads (NIR, Red, Green, Blue)	4
Focal length	120 mm
Pixel size	0.012 mm
Resolution	13824 × 7680 pixels

The aerial images were captured during leaf-on season in May-August 2012. The altitude was 4800 m above ground with a 60% along-track and 30% across-track overlap, producing a Ground Sampling Distance (GSD) in the panchromatic spectrum of 0.48 m. Before the aerial images were provided, Lantmäteriet preprocessed them. The images were block triangulated using bundle adjustment (Triggs et al. 1999) and fitted into the Swedish coordinate system SWEREF 99 TM (EPSG: 3006). In addition to the aerial images, triangulation data in PATB (.ori) format was delivered. This data contained information about image ID, focal length, image coordinates (X, Y and Z) in SWEREF 99 TM and a

3 × 3 rotation matrix describing the image-to-ground relationship (Lantmäteriet, 2013a). The image location uncertainty in terms of RMSE is < 0.6 m in the horizontal and < 0.8 m in vertical direction (Lantmäteriet, 2013a).

Method

Area-based approach

In the current study, an area-based approach was used. The goal of the area-based approach is to map predicted forest variables such as stem volume and basal area in a wall-to-wall estimation (Næsset, 2002). The implementation of the area-based approach in the current study consisted of two phases. First, aerial images were acquired over the entire study area and point clouds were derived using a SGM algorithm. Data from the ALS were used to create a 2 m × 2 m DEM. Then, the height of the point cloud was normalized by subtracting the height of the DEM from the point cloud. Each plot was clipped against the SGM point cloud and descriptive statistics (metrics) were calculated. OLS models were developed where plot attributes, e.g., *HGV*, *DGV*, *VOL* and *BA* were defined as response variables. The metrics were calculated from the clipped point cloud and they correspond to OLS model predictors. In the second phase of the area-based approach, the OLS models were applied to the entire area and rasters corresponding to the independent variables were created. A raster resolution of 14.2 m × 14.2 m was chosen so that the cell size aproximately corresponded to the 200 m^2 plot size. Each individual metric used in the OLS models were represented by an individual raster. The regression functions from the OLS models were then applied in a final step; this resulted in rasters for *HGV*, *DGV*, *VOL* and *BA*. An average of the raster cells within each polygon (stand) was added to the attribute table.

Image matching

In the current study, the software package Surface Reconstruction (SURE) was used for image matching. SURE implements a modification of the SGM algorithm proposed by Hirschmüller (2005 & 2008), in more depth described in Rothermel et al. (2012). Figure 2 shows the workflow of photogrammetric point cloud generation using SURE.

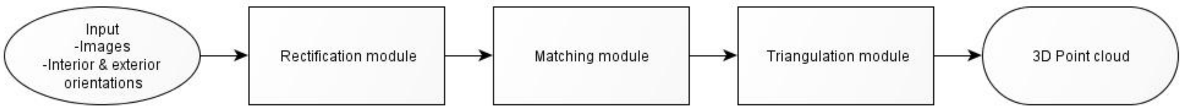


Figure 2. Overview of the implemented workflow for point cloud generation using SURE (Rothermel et al. 2012).

Image rectification

As a lead-in to the rectification module, stereo models (base image and match image) were chosen based on exterior orientation of the images. The stereo models were later on used in the reconstruction process of the images. The goal of image rectification is to speed up the upcoming matching process. This was done so that corresponding pixels in the base image and match image can be found on the same row in the two images, in other words; the epipolar lines are horizontal (Rothermel et al. 2012).

Matching module

The SGM is a pixel-wise matching algorithm which tries to find corresponding pixels in the stereo models. This is done by minimizing a similarity measure, i.e., a global cost function under the assumption that a minimal matching cost is consistent with an optimal pixel correspondence (Hirschmüller, 2008). In Hirschmüller (2008) Mutal Information was proposed as a matching strategy, but in the SGM implementation in SURE Census correlation was used. The global cost function was calculated under a smoothing constraint to ensure a smooth surface reconstruction. Because of the initial image rectification step, the cost function can be estimated in 1D along the epipolar line instead of in 2D, which otherwise would be Non-deterministic Polynomial-time complete (NP-complete) and consequently very time consuming to solve (Hirschmüller, 2008). The cost for potential corresponding matches were then stored in a 3D-cost structure, but since the cost minima is not distinctive, a problem with wrong disparity estimation arises. This was solved by aggregating the matching costs calculated from 16 image paths (Rothermel et al. 2012), and finally the path with the minimum cost was chosen. This was done for all the pixels in the matching image which resulted in a parallax image.

Triangulation module and point cloud generation

Given the parallax image from the matching module and the internal and external orientation for the camera, height of the visible surface in each pixel was assessed using triangulation of the pixels resulting in a 3D point cloud (coordinates in X, Y and Z). Since the matching was done in stereo models the resultant point clouds were merged together in a final step. This was done using the software lasmerge from the open source library libLAS (Butler et al. 2010). The point cloud density is based on the resolution in the aerial images. Due to the pixel-wise matching and the 0.48 m resolution in the panchromatic spectrum a point cloud with a density of about 4 points/m^2 was attained (Figure 3). To cope with hardware limitations, the matched image point clouds were tiled in 1000 m × 1000 m tiles using lastile (Isenburg, 2013).

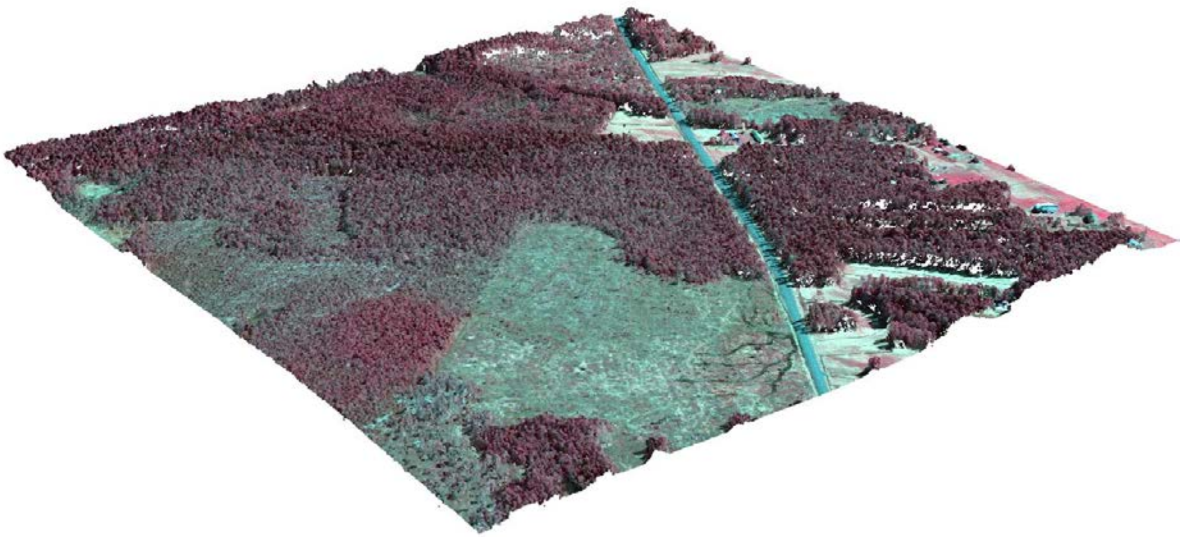


Figure 3. The final result from the SURE workflow, a point cloud with coordinates in X, Y, Z and spectral information in NIR, Red and Green.

Digital elevation model

The method developed in the current study assumes that there is a high resolution DEM available. Therefore, a DEM was created using the software GridSurfaceCreate provided in the software package Fusion 3.20 (McGaughey, 2012). Since the minimum ALS point density was about 0.5 points/m^2 (Lantmäteriet, 2012), the resolution of the DEM is 2 m × 2 m. Each cell in the DEM corresponds to the average height of the classified ground returns within each pixel.

Metrics

A series of metrics were extracted from the matched image point cloud using the statistical package R (R Core Team, 2013). As a first step, the point clouds were normalized using a DEM originating from the ALS point cloud. The normalization is an important step, since the height of the point cloud is initially calculated as height above the geoid. Therefore, it is essential to transform the height of the points so that they correspond to height above ground instead of height above the geoid. The points were then clipped using the centroid coordinates from the field plots and a plot radius of 8 m. Point cloud metrics were then calculated.

Height metrics

Many of the metrics originated from the vertical structure of the point cloud and were developed for variable estimation using ALS data. In the current study, percentile metrics were used to describe the canopy height. Percentiles (p_{10}, p_{20}, ..., p_{95}, p_{100}) corresponding to the 10, 20, …, 95 and 100 quantiles of the point height distribution and were calculated along with standard deviation, *STD* (Eq. 1) and coefficient of variation, *CV* (Eq. 2).

$$STD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{1}$$

$$CV = \frac{STD}{\bar{x}} \tag{2}$$

Density metrics

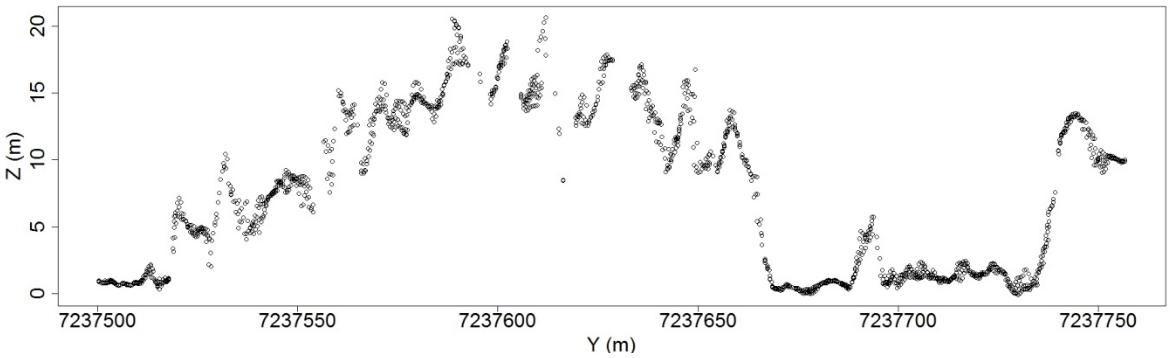
Density metrics have been widely used together with percentiles to estimate forest variables (Næsset, 2002; Holmgren, 2004). Nilsson (1996) was the first to define a threshold (2 m) and with that separated vegetation hits from understory vegetation hits resulting in a vegetation ratio metric. The image matched point cloud lacks height measurements under the canopy (Figure 4). Bohlin et al. (2012) explored different thresholds from 2 - 5 m and found that a higher threshold yielded results with lower RMSE in the forest variable estimations. Accordingly, a 5 m threshold was chosen for vegetation ratio (D_5) calculations in the current study (Eq. 3).

$$D_5 = \frac{n_{\text{veg}}}{n_{\text{total}}} \tag{3}$$

n_{veg} = Number of returns above the threshold (5 m)
n_{total} = Number of total returns

Canopy cover
Canopy density metrics from the image matched point cloud are not expected to explain as much of the variance in stem volume related estimation as the ALS counterpart (Nurminen et al. 2013). A disadvantage of the D_5 in a photogrammetric context is that it is based on the assumption that there are points representing the ground present in the point-cloud. While using aerial image matching this is not usually the case (Figure 4).

Semi-Global Matching (a)



Airborne laser scanner (b)

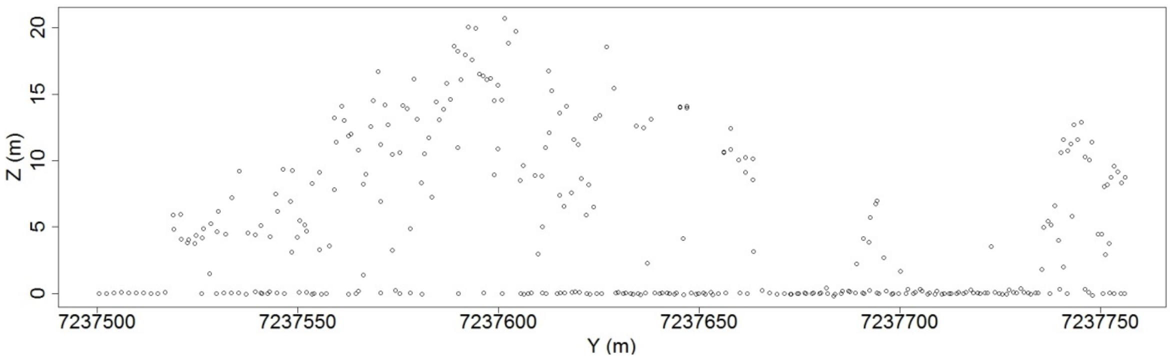


Figure 4. Cross sectional view of the two different point clouds. (a) shows an SGM transect with a point density of 3.51 points/m^2 and (b) shows an ALS transect, with a point density of 0.66 points/m^2.

In order to be able to triangulate the height of an object it has to be seen in two images that are overlapping. In some cases, ground is visible in one image but occluded in the other. In this case, the matching algorithm fails to identify a parallax and therefore omits a height measurement. Thus, the lack of information may itself contain information. A fundamental assumption of the vegetation ratio, D_5, (Eq. 3) is that ALS returns are derived from either ground/understory vegetation or vegetation returns above the defined threshold. Consequently, a lack of returns is not accounted for.

In pursuit of additional independent variables Bohlin et al. (2012) explored horizontal texture metrics proposed by Haralick et al. (1973) and found that texture metrics contributed to a lower RMSE at stand level for stem volume and basal area estimates. It is therefore likely that horizontal metrics may provide additional information in stem volume related estimates.

Stem volume estimates using aerial images have previously been carried out by manual interpretation of height and canopy cover in stereo viewed images. These explanatory variables have been used in stand stem volume functions (Eid & Næsset, 1998; Åge, 1983). It is thus established that there is a positive correlation between canopy cover (Figure 5) and stem volume. As a result of this an additional variable was examined in the current study; a horizontal metric similar to the canopy cover metrics.
"*Canopy cover refers to the proportion of the forest floor covered by the vertical projection of the tree crowns*" (Jennings et al. 1999, p.62)

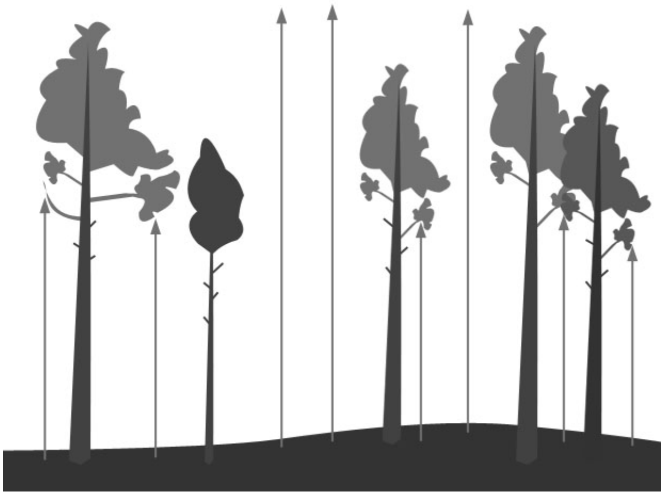


Figure 5. An example of measure of canopy cover.

To estimate the canopy cover a 2D kernel density estimation of the points was implemented using the MASS package in R (R Core Team, 2013). Points with a height over the 5 m threshold were placed on a 100 × 100 grid. An axis-aligned bivariate normal kernel with a bandwidth of 1 was placed on every point in the rectangular grid and the density was summed over all the kernels within each grid. The bandwidth was chosen subjectively with support of contextual knowledge about the data (Tukey, 1977) and the contour lines given in Figure 6.

Canopy Cover (*CC*) was estimated as the number of grid cells with a density greater than a predefined threshold (T_{DL}) corresponding to one of the levels of the density contour lines (0.001 - 0.005), divided with the total area calculated as a circle due to the shape of the plots, given in Eq. (4). The canopy cover was denoted as CC_1, CC_2,…,CC_5, where the density levels 0.001 - 0.005 are represented by integers 1 - 5. The number of grid cells (N) in X and Y direction corresponds to the diameter used in the *CC* calculation.

$$CC_T = \frac{\sum_{i=1}^{N}(x_i > T_{DL})}{\left(\frac{\sqrt{N}}{2}\right)^2 \pi} \qquad (4)$$

N = Number of grids cells
x_i = Density of cell number i
T_{DL} = Threshold corresponding to density levels 0.001 - 0.005

(a) (b)

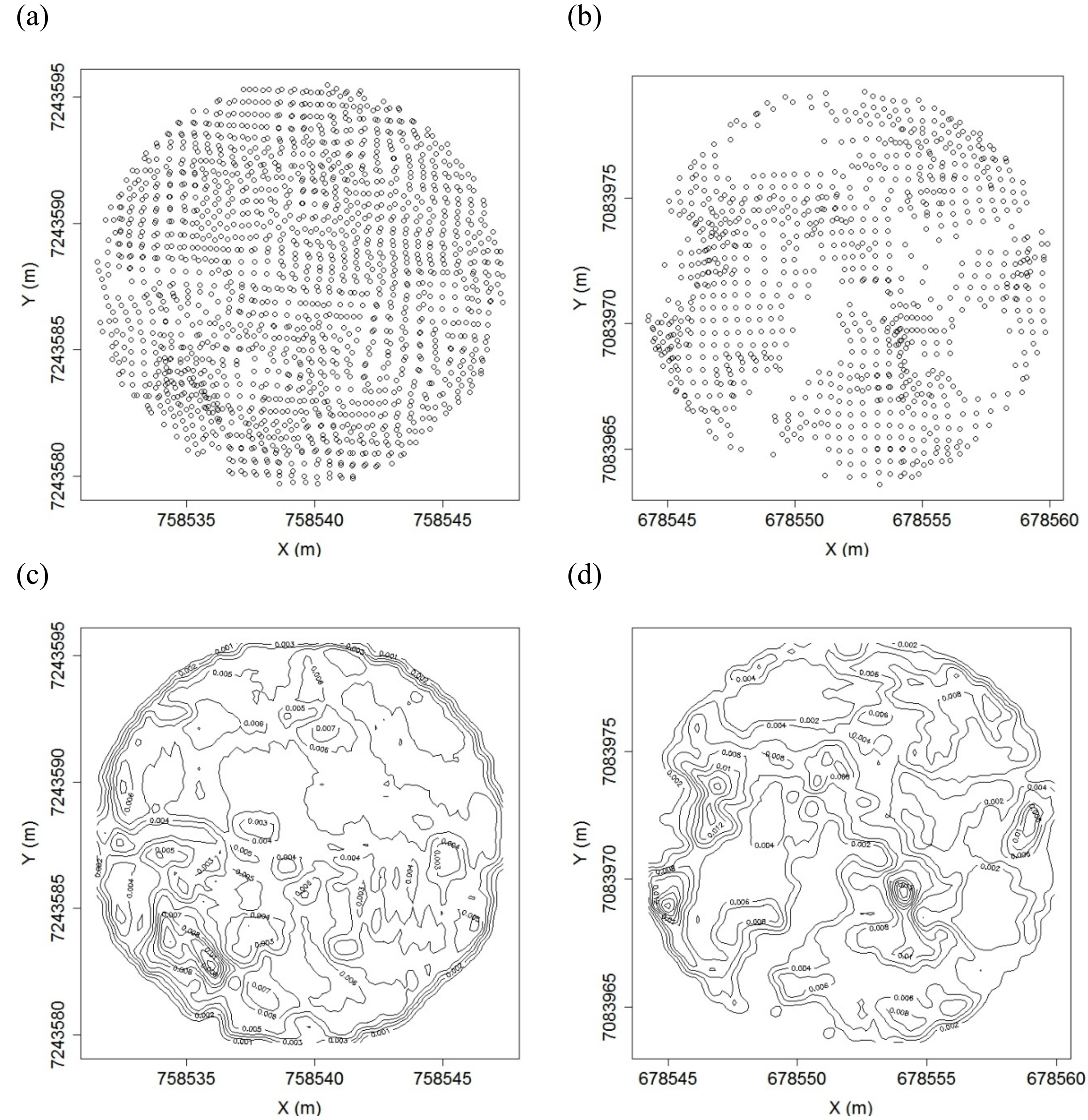


Figure 6. A visual illustration of the density estimation contours. The points are distributed in X-Y direction, i.e., shown from above. The thresholds T are shown as contour lines. (a) and (c) in the left column indicate a plot with little or no gaps in the canopy cover and accordingly a canopy cover close to 1 (0.93 at the 0.003 level, e.g., CC_3). (b) and (d) show a canopy cover with gaps resulting in a canopy cover of < 1 (0.75 corresponding to the 0.003 level, e.g., CC_3).

Modeling

Using regression analysis a number of a priori assumptions regarding the relationship between the dependent and independent variables have to be made. For example, errors are normally distributed, independent, have a mean zero and have the same but unknown variance. The model which describes the data should be linear (Chatterjee & Hadi, 2006).

The dependent variables in the regression of stem volume and basal area have an exponential relationship to the explanatory variables. The relationship can be described as a concave function and this is considered a violation against the above stated rule about the linearity of the model. To solve this problem, a logarithmic transformation converts the relationship to its linear equivalent and stabilizes the variance about the regression functions (Li et al. 2008). This enables the use of the least square regression and fulfills the general assumption about linearity (Chatterjee & Hadi, 2006) (Figure 9). The models of n_p independent variables can be formulated as:

$$ln(Y_i) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_{n_p} X_{in_p} + \varepsilon_i \tag{5}$$

where Y_i is *VOL* (m^3/ha) or *BA* (dm^2/ha).

One goal during modeling was to create simple models. Only variables with a p-value < 0.05 were included in the model (Chatterjee & Hadi, 2006).

After the regression the estimated values were transformed back to the original scale. This procedure inherent negative biases because the largest values are compressed on the logarithmic scale, which reduces the leverage for large values (Beauchamp & Olson, 1973). In the current study, a correction factor (*CF*) proposed by (Snowdon, 1991) was used for correcting the negative bias in the estimates:

$$CF = \frac{\sum_{i=1}^{n} z_i}{\sum_{i=1}^{n} \hat{z}_i} \tag{6}$$

where Z_i are the sampled data of either stem volume or basal area, $\hat{Z}_i$ are the corresponding predicted logarithmic values from the regression transformed back to the original scale, and n is the number of sample plots. As a final step the estimated values from the cross-validation were multiplied with *CF*.

Feature selection

To assess the goodness of fit the coefficient of determination (R^2) and the adjusted R^2 were evaluated. Plot level estimation accuracy was determined by absolute and relative RMSE Eqs. (7) and (8). Independent variables were selected based on the correlation with the dependent variables, regression statistics, estimation bias, Eqs. (9) and (10), and RMSE performance.

Plot level accuracies were assessed using leave-one-stand-out-cross-validation. Since it is likely that sample plots within the same stand have similar attributes, all observations within the same stand were excluded from the data set and the rest of the observations (n-stand$_i$ out of n plots) were used as training data. This procedure was repeated until each stand was used once as validation data. The results were then evaluated on plot level in terms of RMSE and bias. To evaluate overfitting, i.e., if the statistical models describes the random error instead of the underlying relationship, the square root of the ratio between the predicted sum of squares of residuals and the ordinary sum of squares of residuals, denoted q, was calculated (Weisberg, 1985).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad (7)$$

$$\mathrm{RMSE}[\%] = \frac{\mathrm{RMSE}}{\bar{y}} \cdot 100 \quad (8)$$

$$\mathrm{Bias} = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n} \quad (9)$$

$$\mathrm{Bias}[\%] = \frac{\mathrm{Bias}}{\bar{y}} \cdot 100 \quad (10)$$

where:
y_i = Observed value
$\hat{y}_i$ = Predicted value from leave-one-stand-out-cross-validation
$\bar{y}$ = Mean of the observed values
n = Total number of sample plots

Segmentation

The segmentation was carried out on a 3 m × 3 m raster based on the maximum height, e.g., the 100th percentile from the photogrammetric point cloud where pixels with a height < 5 m were excluded. The segmentation approach consists of three phases. First, an edge preserving smooting Anisotropic Diffusion algorithm was applied, second, a Mean Shift segmentation. The segmentation was finally clipped by road, agricultural and water layers from the Lantmäteriet's property map (Lantmäteriet, 2014). Both the Anisotropic Diffusion algorithm and the Mean Shift segmentation is available in the open source software package ORFEO toolbox (CNES, 2013).

Mean Shift is a density estimation-based non-parametric clustering approach and considers feature space as an empirical Probability Density Function (PDF). The method was first invented by Fukunaga & Hostetler in 1975. The technique was then largely forgotten until it was rediscovered by Chen (1995). In the current study, a further development of the Mean Shift algoithm by Comaniciu & Meer (2002) was used. If the PDF f(x) can be computed and major peaks (modes) can be found, it would be possible to identify clusters associated with the given modes. These kinds of methods are often referred to as gradient assents. A more intuitive description could be done with an analogy; consider the PDF as a mountain landscape. Each point is represented by a hiker. Each hiker aims to climb the closest peak (mode). All hikers who reach the same peak are considered part of the same cluster. One way to estimate the PDF is by a Parzen windows technique where a kernel G(x) is placed on every sample from the underlying PDF. The Kernel Density Estimate (KDE) is obtained by convolving the sparse set of input samples (x_i) with a fixed kernel width (Figure 7). A problem with this method is that it is computationally intensive even at lower dimensions (Szeliski, 2010). Therefore, Mean Shift uses a variant where the PDF is never calculated. Instead, the Mean Shift algorithm starts at a random point (x_t) and calculates the gradient using a window with a user defined radius, then moves the windows to the calculated mean (x_{t+1}) and iterates until it reaches a mode. Comaniciu & Meer (2002) proved that the Mean Shift vector (direction from x_t to x_{t+1}) always points towards the maximum in PDF and converges at the mode.

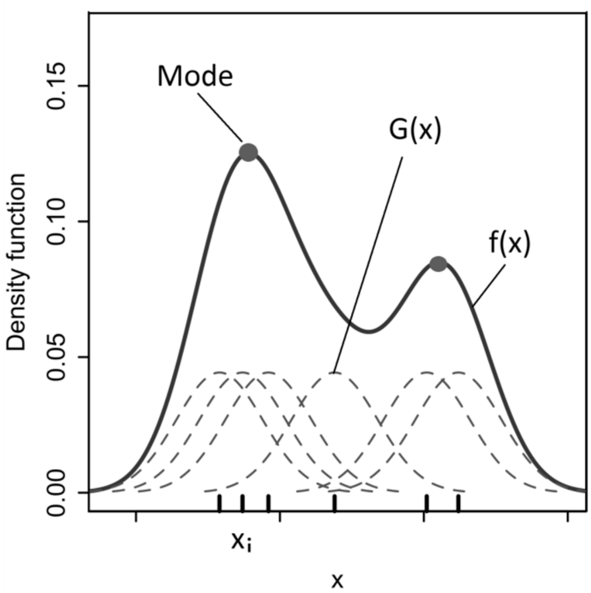


Figure 7. One dimensional visualisation of the kernel density estimation and mode localisation. x_i (i = 1, 2, 3, …, n) are the samples from the underlying population and over every x_i a kernel G(x) is placed. The summation of all kernels results in a KDE f(x).

The Mean Shift implementation of Comaniciu and Meer (2002) searches for modes in both the joint feature and spatial domain. This means that the spatial coordinates of the image (X, Y), i.e., the spatial domain, are concatenated with the values in the range domain, in the current study, the 100th percentile. This makes it a total of n+2 dimensions. An iterative procedure of mode seeking consists in shifting the n+2 dimensional window to a local mode. When the Mean Shift vector is approaching the mode, the vector speed decreases. The peak is considered found when the vector movent is below a predefined threshold or the number of iterations reaches the stop limit. The window involves two user defined separate parameters; h_s and h_r. The input parameters control the spatial and range bandwiths of the filter kernel and the selected input parameters have a large effect on the outcome. To determine the best bandwidth parameters (h_r and h_s) is decribed somewhat like an art (Szeliski, 2010; Chehata et al. 2011).

Results

Data preprocessing

The method Cook's distance, proposed by Cook (1977), was used to examine individual plots' influence in the current study. Chatterjee and Hadi (2006) suggest that rather than using a fixed threshold for exclusion of influential plots, a visual interpretation is preferrable. A measure of influence of *DGV* estimation is shown in Figure 8.

Measure of influence

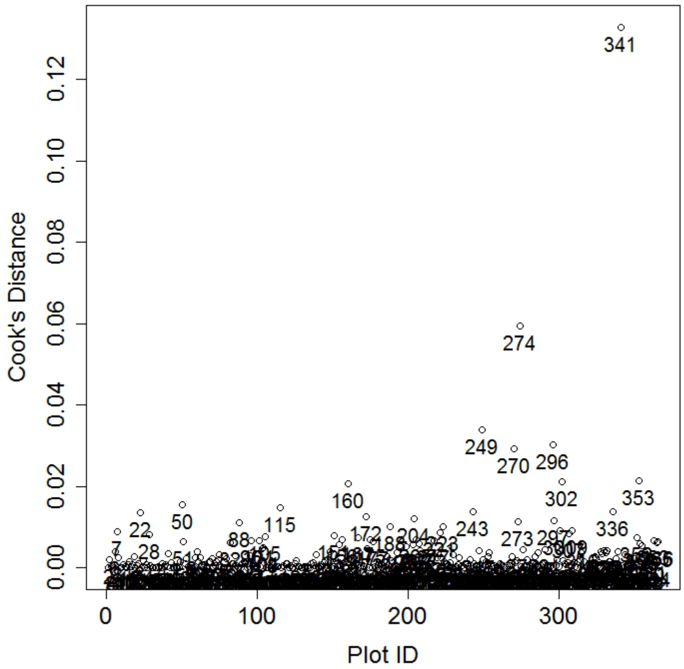


Figure 8. Plot ID is plotted against Cook's distance for *DGV* estimation.

Compared to the main part of the plots, plot ID 341 has a marked increase in the measured value of Cook's distance. In a further investigation of the deviant plot, it was found that it was a single non-representative deciduous and that it skewed the *DGV* value for the plot. Thus, plot ID 341 was excluded.

Since the *HGV* and *DGV* estimations did not show any sign of breaking the assumption about linearity or heteroscedasticity (Figure 9), no transformation had to be done and a general formula for *HGV* and *DGV* could be expressed as Eqs. (11) and (12).

$$HGV = \beta_0 + \beta_1 X_{i1} + \varepsilon_i \qquad (11)$$

$$DGV = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \varepsilon_i \qquad (12)$$

After the logarithmic transformation of *VOL and BA* the variance stabilized and the trend of heteroscedasticity was reduced (Figure 9).

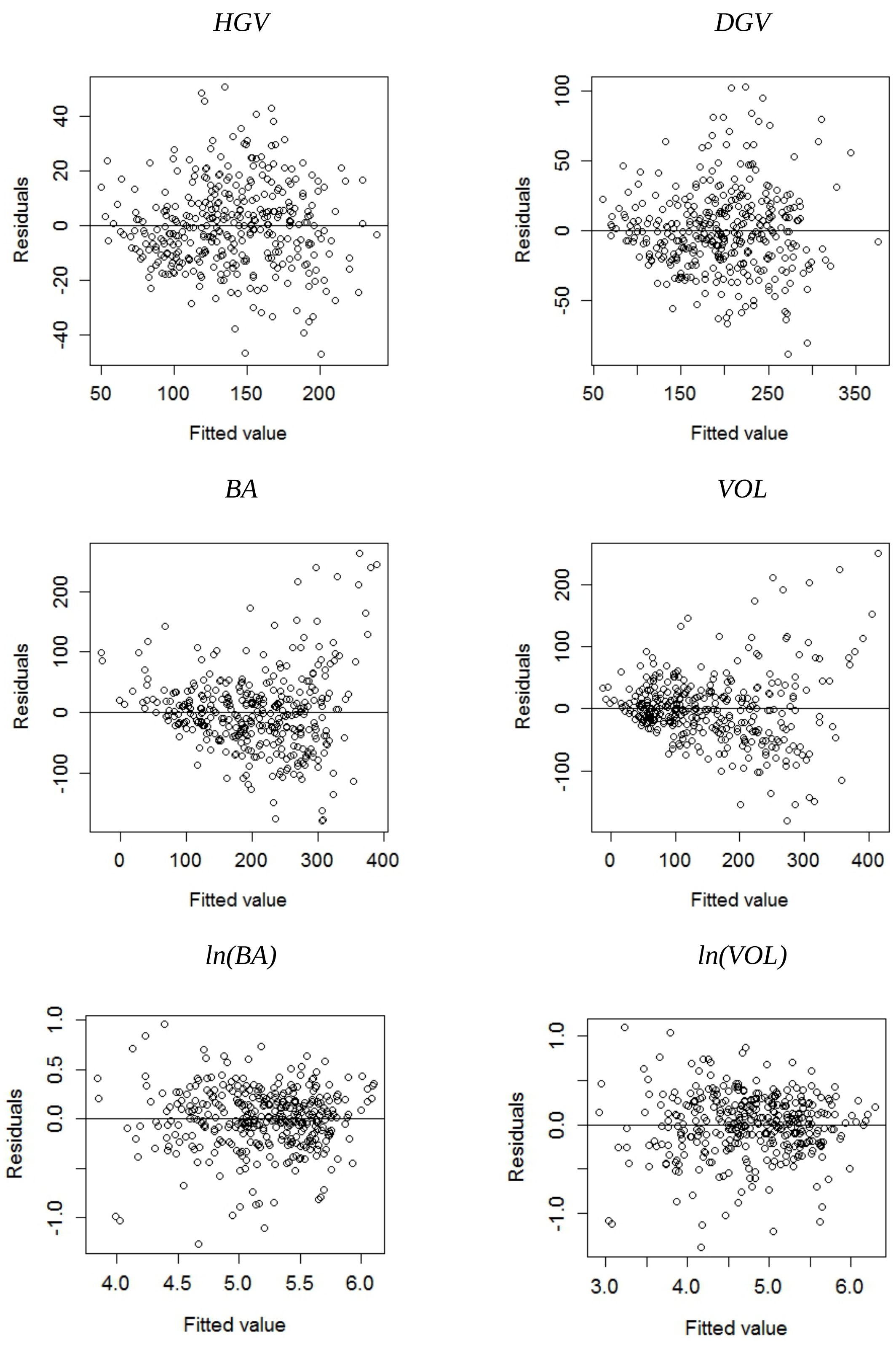


Figure 9. Fitted values plotted against residuals for *HGV*, *DGV*, *BA*, *VOL*, *ln(BA)* and *ln(VOL)*.

Plot level accuracies

The accuracies for the *HGV* and *DGV* estimates derived from the matched image point cloud are presented in Table 5. In the *HGV* estimation, 86.0% of the variance was explained by the $p_{95,}$ resulting in a relative RMSE of 11.2%. In the *DGV* estimation a multiple linear regression with the independent variables p_{95} and *CV* explained 78.8% of the variance of *DGV,* with a relative RMSE of 15.2%. All the variables had a significance level with $p < 0.001$.

Table 5. Plot level accuracies for basal weighted mean height (*HGV*) and basal area weighted mean diameter (*DGV*)

Estimated variable	**Independent variables**	**Value**	**CF**	**Bias**	**Bias (%)**	**RMSE**	**RMSE (%)**	**R^2-adj (%)**	***q***
HGV	Intercept***	37.48	N/A	0.04	0.03	15.6	11.2	86.0	1.01
	p_{95}***	8.20							
DGV	Intercept***	11.66	N/A	0.01	0.01	29.9	15.2	78.8	1.01
	p_{95}***	13.40							
	CV***	51.07							

Codes of significance: $p \leq 0.001$ '***' $0.001 < p \leq 0.01$ '**' $0.01 < p \leq 0.05$ '*'

Two models for stem volume and basal area are presented in Table 6. Model 1 includes a horizontal CC_3 metric and Model 2 includes only vertical metrics. The relative RMSE for *VOL* estimation is 33.5% for Model 1 and 36.3% for Model 2. The corresponding results for *BA* is 30.3% for Model 1 and 33.1% for Model 2. The difference in RMSE between stem volume estimates for Model 1 and Model 2 is -4,2 m^3/ha (-7.7%) and for basal area -5.9 dm^2/ha (-8.7%). All models include a measure of variability, in 3 of 4 models are *CV* used, however, in Model 2 is *STD* used in the stem volume estimation and was significant ($p \leq 0.05$). The intercept was significant ($p < 0.001$) for all models. The *q*-values from the cross-validation test confirmed that these models were not overfitted ($q \leq 1.02$).

Table 6. Plot level accuracies for stem volume (*VOL*) and basal area (*BA*) estimates. Two models are presented with different density metrics: Model 1 includes the CC_3 metric as independent variable and Model 2 includes D_5 as independent variable

Estimated variable	**Independent variables**	**Value**	**CF**	**Bias**	**Bias (%)**	**RMSE**	**RMSE (%)**	**R^2-adj (%)**	***q***
Model 1									
VOL	Intercept***	3.00	1.05	0.00	0.00	50.6	33.5	77.5	1.02
	p_{95}***	0.12							
	CC_3***	0.67							
	CV*	-0.26							
BA	Intercept***	4.11	1.04	-0.26	-0.13	61.9	30.3	66.8	1.02
	p_{95}***	0.06							
	CC_3***	0.65							
	CV***	-0.34							
Model 2									
VOL	Intercept***	3.07	1.05	-0.54	-0.36	54.8	36.3	77.9	1.01
	p_{95}***	0.10							
	D_5***	0.76							
	STD*	-0.04							
BA	Intercept***	4.29	1.05	-0.95	-0.47	67.8	33.1	65.4	1.01
	p_{95}***	0.05							
	D_5***	0.52							
	CV**	-0.33							

Codes of significance: $p \leq 0.001$ '***' $0.001 < p \leq 0.01$ '**' $0.01 < p \leq 0.05$ '*'

In Figure 10-12 are surveyed plot variables plotted against estimated values. An aspect line with a slope of 1:1 is included as a reference.

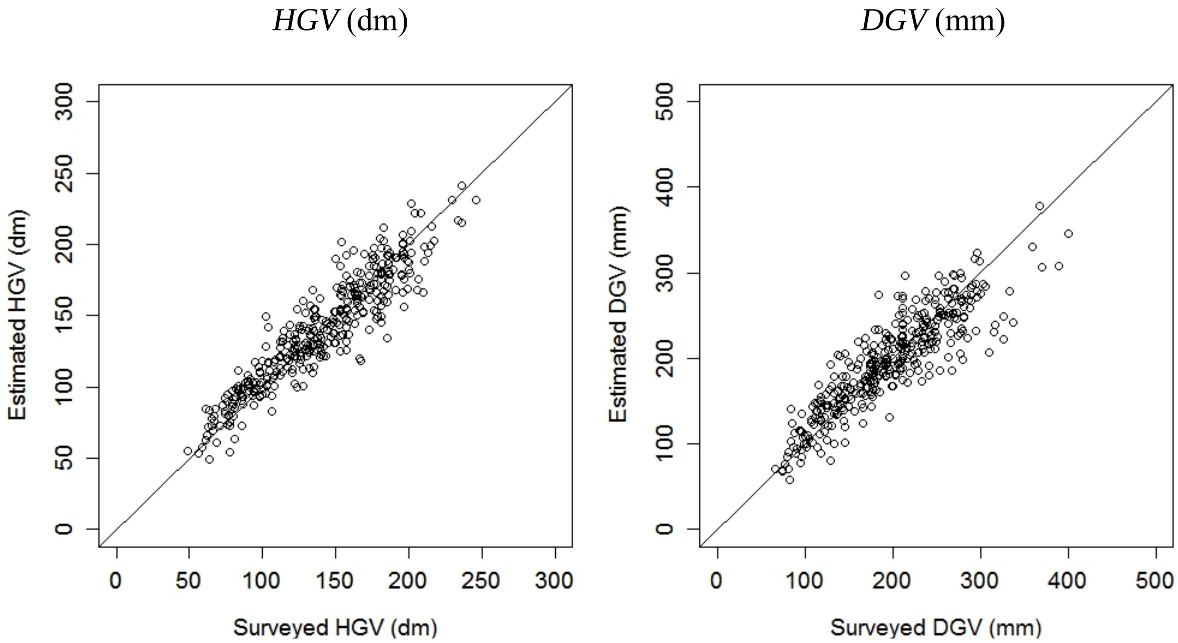


Figure 10. Scatterplots of surveyed values of *HGV* and *DGV* plotted against estimated values.

VOL (m^3/ha)

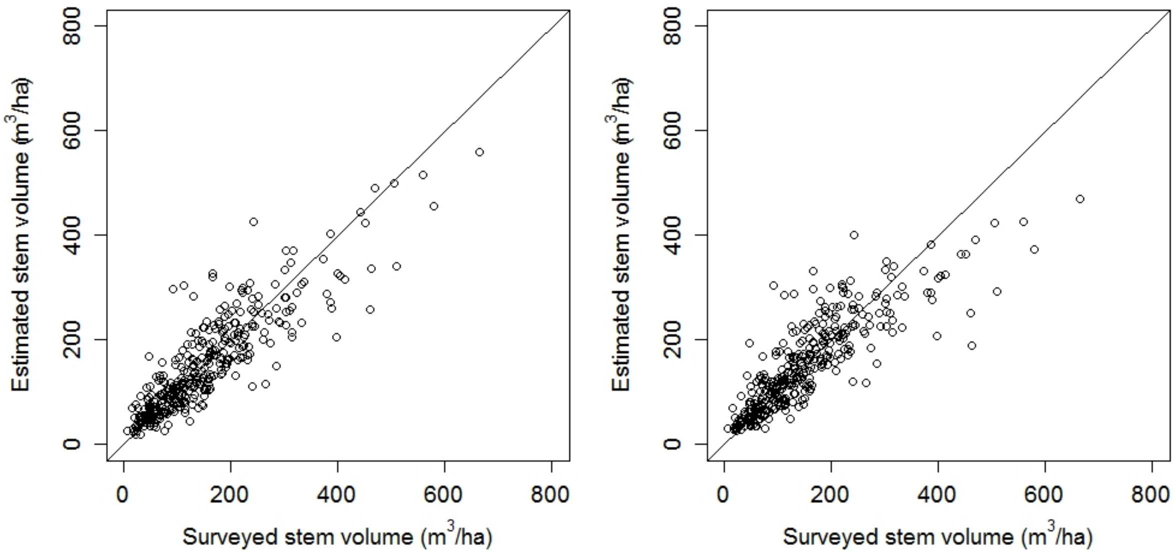


Figure 11. Surveyed stem volume plotted against estimated stem volume for Model 1 using CC_3 metrics to the left and Model 2 using D_5 to the right.

BA (dm^2/ha)

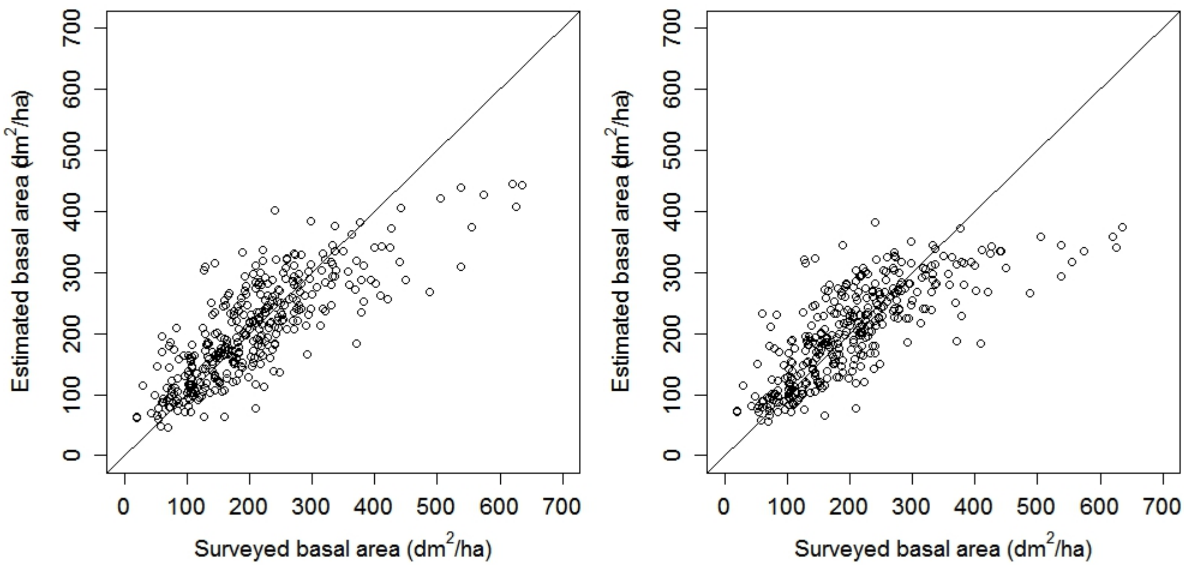


Figure 12. Surveyed basal area plotted against estimated basal area for Model 1 using CC_3 metrics to the left and Model 2 using D_5 to the right.

Values of VOL over 300 m^3/ha and BA over 300 dm^2/ha appears to be underestimated using both Model 1 and Model 2. However, the tendency is greater for estimations using Model 2 and particularly evident in BA estimates.

Segmentation result

Figure 13 shows the result from the Mean Shift segmentation given the segmentation settings in Table 7. The area is 6522 m in East-West direction and 9168 m in North-South direction resulting in an area size of 5979 ha. The area contains 1547 stands with an average stand size of 3.8 ha. Each of the polygons contain information about*; ID, Area, HGV*, *DGV*, *VOL* and *BA.*

Table 7. Settings for Mean Shift segmentation

Segmentation	h_r	h_s	Threshold	Minimum size (n pixels)	Max iterations
Mean Shift	0.5	5	0.01	1111	100

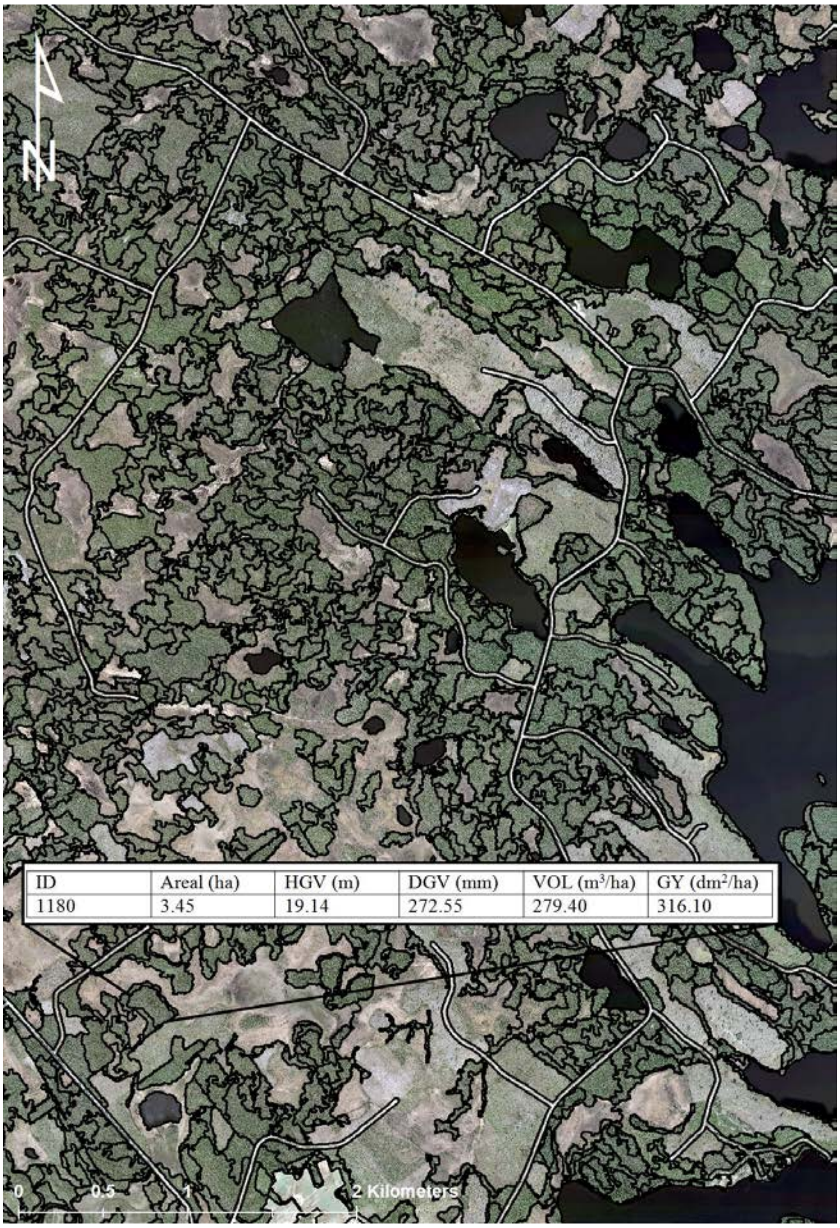


Figure 13. Output from the segmentation approach. Every polygon contains information about polygon ID, Area, *HGV*, *DGV*, *VOL* and *BA*. © Lantmäteriet

Discussion

The purpose of the current study was to create a DST using stereo images matched with an SGM algorithm. The reliability of the DST depends on how accurately the forest variables *HGV*, *DGV*, *VOL and BA* are estimated. In order to obtain good estimations, different metrics were investigated; in a first test, metrics developed for the purpose of forest variable estimations using ALS was tested. However, stem volume and basal area estimates showed undesirable properties using solely ALS metrics, namely a systematic underestimation of *VOL* and *BA* estimates over 300 m^3/ha and 300 dm^2/ha. Therefore, a new metric was investigated; canopy cover. Model 1 which contains the *CC* metric lowered the RMSE with -4.2 m^3/ha (-7.7%) for *VOL* and -5.9 dm^2/ha (-8.7%) for *BA* in comparison with the Model 2 which contains the D_5 metric. Estimations using *CC* metrics also decreased the declining trend for both *VOL* and *BA* estimates even though this trend was more salient for *VOL* estimates. In order to meet prevailing practice in Swedish forestry, an automatic segmentation using a Mean Shift algorithm was performed. Due to the limited time frame, no qualitative validation of the segmentations was done. However, when setting the segmentation parameters, the result was assessed subjectively and the parameters were configured so that the average stand size corresponded to normal practice; 2 - 5 ha (Holopainen & Talvitie, 2006). The results were implemented in the proposed DST for wood procurement planning.

However, there are some aspects of the methodology that should be taken into consideration when interpreting the results. In order to achieve a smooth surface reconstruction, the SGM algorithm uses a smoothing constraint which has implications on the final result, e.g., trees on a clear-cut area are usually smoothed and the tree height is usually underestimated. This could have a negative effect on the forest variable estimates, especially on applicable clear-cut areas.

A more general feature affecting the results is the parallax measurement. In order to correctly measure the parallax, the matched object needs to be fixed, e.g., found on the same position in the two images. In windy conditions, treetops might move between the two camera shoots, resulting in an erroneous height measurement.

If the OLS models are applied outside the range of the study area (63.5° N - 65.2° N), additional validation has to be performed, and if necessary, recalibration of the models. Regression models generally perform best within the range of the training data, and more poorly when forced to extrapolate beyond the range of the training data (Chatterjee & Hadi, 2006; Maltamo et al. 2011). In the current study, the *HGV* range is between 49.0 - 246.0 dm (Table 3). Since there are no measurements when the *HGV* is less than 49.0 dm, the intercept was found to be highly significant in the regression models. In order to avoid bias in a wall-to-wall estimation it is recommended that height measurements < 49.0 dm are masked since these areas are likely to be overestimated. Estimation above the range of the field plots given in Table 3 are also extrapolated and inherit a greater risk to be biased.

As previously mentioned, SCA's survey was not specifically performed for the current study. Thus, some remarks about the plots can be made. Field work is costly and the plot size is an important consideration. Smaller plots have a higher perimeter-to-area ratio and consequently include more edge related elements. This makes smaller plots more sensitive to the GPS-accuracy while larger plots are more costly due to increased field work

(White et al. 2013b). Frazer et al. (2011) showed that biomass prediction improved markedly as the plot size increased. With this in consideration, the plot size used in the current study is smaller than plots in comparable studies (Table 1).

Gobakken & Næsset (2009) studied the relationship of position error and estimation accuracies, and concluded that the estimation accuracies were not affected to any great extent when the position error was up to 5 m. Their results can be compared to the current study's sub meter plot accuracy. As a conclusion, the design of the survey meets the requirements for material used in studies in the field of forest remote sensing with regard to stratification, GPS-accuracy and plot size (White et al. 2013b).

In order to improve the stem volume estimation, calculation of additional independent variables could potentially improve the stem volume estimation. A possible addition, which was not investigated due to the limited time frame of the current study, might be to include a texture measurement (Haralick et al. 1973) as proposed by Bohlin et al. (2012) in combination with the *CC* metric proposed in the current study. One additional possible improvement would be to include a variable that is connected to the amount of deciduous tree species. Since all metrics derived from image match point clouds are sensitive to top canopy properties is it likely that the phenological differences between hardwood and softwood introduces a bias, foremost in stem volume and basal area estimates. Straub et al. (2013) found that in mixed forests in southern Germany the stem volume and basal area estimates were improved by implementing tree species stratification.

Reliability

It is essential for the reliability of the DST that it provides the end user with highly accurate forest variable estimates. The results from the current study indicate that 3D data from the matched aerial images using SGM can accurately estimate important forest variables, provided that an accurate DEM is available. A comparison with available peer reviewed articles with both image matched point clouds and ALS are presented in Table 1. The result of the *HGV* estimation in the current study is well in line with previous research with matched image point clouds and comparable with the results achieved by ALS (Holmgren, 2003). The *DGV* estimations are also comparable with results from ALS (Næsset, 2004). The relative RMSE of the *VOL* estimation is higher than the results in the study by Nurminen et al. (2013), but somewhat lower than in the study by Järnstedt et al. (2012) and Straub et al. (2013) (Table 1). The difference between the results can be related to differences in study areas, plot sizes, features describing the plots, matching algorithms and forest structures.

Canopy cover

One issue that was addressed in the current study is the difficulty of making stem volume estimations using image matching due to the absence of penetrating measurements in the canopy. Therefore, a *CC*-related variable was introduced.

Different thresholds were examined and the 0.003 level proved to be most significant. One explanation to this phenomenon could be that larger threshold values have a reduced tolerance for outliers and capture a more general extent of the canopy. However, it should be noted that the difference between the different *CC* levels were small. The declining trend was more prominent for *BA* compared to *VOL* estimates. This would indicate that density metrics have a larger effect on the estimated values for basal area compared to stem volume.

In general, *CC* metrics were more influential in *VOL* estimation in comparison to D_5. One possible explanation for the difference between *CC* and D_5 is the capability of the *CC* metric to utilize the lack of information, i.e., where the SGM algorithm fails to identify a similarity due to occlusion and therefore omits a height measurement. This could be the circumstance when one camera is able to identify the ground, but because of the divergent viewing angle of the second camera, the line of sight is obscured and the SGM algorithm cannot match the two corresponding pixels. The D_5 does not consider this feature while the *CC* does.

An important consideration while using the *CC* variable introduced in the current study, is the settings for the image matching algorithm, since *CC* is sensitive to changes. Some SGM algorithms implemented in commercial software have an interpolation feature which interpolates gaps in the point cloud. Such features would degrade the performance of the *CC* metric in stem volume estimations.

Even though *CC* metrics improved the results, facts remain; the vertical structure is the single largest explanatory variable in stem volume related estimations using image matching. Nurminen et al. (2013) used a non-parametric (Random Forest) approach and showed that vegetation ratio using ALS had almost three times larger relative feature importance compared to the image matched derived counterpart in the stem volume estimation.

Practical implications

Given the estimation accuracy, the low cost and the automated workflow the DST proposed in the current study could be an important tool for wood procurement planning in wood procurement organizations. In general, the area-based approach is not dependent on stand segmentation and could be directly applied on plot level. However, plot level estimations are not customary in Swedish forestry. In order to cope with the prevailing methods where forest variables are presented at stand level, an automated segmentation procedure was performed. This is an important step that opens up further possibilities to add additional information to the stands, e.g., mean slope, distance to ground water, distance to nearest road etc. This allows the DST to adapt to the end user's needs.

Since stands are delineated, the output of the DST could be used as a simplified version of a forest management plan. In a qualitative study in which 2500 people were interviewed, it was found that the propensity to harvest was greater with NIPF owners who had a forest management plan (SOU 1981:81). A simple forest management plan can then be based on the output of the DST. NIPF owners with a forest management plan tended to have an increased logging activity, which could result in not just a short term benefit but also a long-term benefit for both procurement organization and NIPF owners.

Future development

Due to the limited time frame of the current study, no subjective assessments of silvicultural decisions like thinning have been performed, even though it would be an interesting feature for a DST. Incorrect harvesting decisions, as delayed thinning, may result in growth and income losses for the forest owners (Agestam, 2009). Subjective assessment of thinning has been performed in earlier studies using ALS (Pippuri et al. 2012; Vastaranta et al. 2011). Due to the similar characteristics of the 3D point clouds related approaches could be tested.

As previously mentioned, there are several matching algorithms available. The proposed *CC* metric is somewhat sensitive to changes for settings in the selected algorithm. A feature based matching algorithm transforms image data into scale-invariant coordinates relative to local features (Lowe, 2004). The result of a feature based image matching algorithm is a less dense point cloud compared to SGM but since no smoothing algorithm is implemented, local extremes are maintained. A feature based matching might therefore improve the performance of the *CC* metric.

The point clouds derived from image matching in the current study consist of coordinates in X, Y and Z, but every point is also colored in NIR, Red and Green. However, no color information has been utilized in the current study. Color information has previously been used in combination with ALS to estimate tree species distribution (Packalén & Maltamo, 2006). Identification of tree species distribution is important for technical, economic and ecological reasons (Korpela, 2004), but it could also possibly contain information about forest health. Therefore, further studies are required to identify the potential of color information in image matched point clouds.

In Sweden, Lantmäteriet has collected nationwide aerial images since 1950 (Lantmäteriet, 2013b) and digital images since 2005 (Lantmäteriet, 2013c). Owing to the long-term plan there is an assured continuity of new images (Lantmäteriet, 2013d). This adds a temporal dimension which could be used to assess for example site index and forest growth. In a study by Eid (2000) the cost of uncertainty in inventory data was estimated. At a rate discount of 3% and a random error of 15% site quality and stand age were found to be the most influential variables for the net present value-losses.

Conclusions

The DST proposed in the current study can be used as a support in wood procurement planning and forest management. Aerial images are an appropriate data source in the proposed DST, mainly because of the readily availability and low cost. SGM proved to be a suitable matching algorithm and created viable point clouds. The current study’s *HGV* and *DGV* estimation results are in line with estimation results using ALS, while the results of *VOL* and *BA* estimations were somewhat less accurate compared to ALS estimations. The *CC* metrics introduced in the current study can be used to improve estimations related to stem volume.

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