Data Collection for Forest Management Planning Using Stereo Photogrammetry

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Cover: The two images at the top are aerial images (©Lantmäteriet) used for stereo photogrammetry and the lower is an oblique view of the resulting tree dimensional point cloud.

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Abstract

Forest managers need information about the forest state for planning treatments. The information needs to be sufficient for the purpose and preferably obtained at low cost and with regular updates. In the last decade, development and use of airborne laser scanning (ALS) for forest variable estimation has been a revolution for forest management planning. But it has also created opportunities for other three dimensional (3D) technologies which can describe the forest canopy surface, since it provides an accurate model of the ground elevation. One such technique is stereo photogrammetry using aerial images. Using aerial images from national image surveying programs, high resolution 3D data and spectral data can be acquired regularly with a frequency of about 2-4 years over forest land in Sweden. The aim was to produce forest variable raster maps which can be used at stand level but also as information to describe within stand variation and updating stand boarders after clear-cut.

In this thesis aerial images from the National Land Survey's image acquisition program has been used in all studies, but also high resolution and highly overlapping images have been evaluated. Using field plots, the 3D and spectral data can be linked by models to predict forest variables of interest. In this thesis; tree height, diameter, basal area, stem volume, species-specific stem volume and species proportions have been the variables of interest. Models have been applied and evaluated at Remningstorp in southern Sweden (Lat. 58°N, Long. 13°E), but also scaled up to national level using field plots from the national forest inventory. The included studies show that aerial images can produce forest variable estimates with good accuracy where best results in terms of root mean square error of the mean were 8.8% for tree height, 14.9% for basal area and 13.1% for stem volume, but that species-specific variables did not perform as well.

In conclusion, aerial images with 0.5 m resolution and 60% overlap using stereo photogrammetry produce estimates with an acceptable level of accuracy for use as a data source for forest management planning. However, very sparse forests, deciduous forests and mature forests have larger estimation errors. Nevertheless, from a forest management perspective, forest information can be collected at very low costs and with high spatial and temporal resolution.

Keywords: area-based approach, aerial images, image matching, multi-spectral lidar, forest variables, species-specific.

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Without stereo photogrammetry life would be pointless.

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 Bohlin J., Wallerman J., and Fransson J.E.S. (2012). Forest variable estimation using photogrammetric matching of digital aerial images in combination with a high-resolution DEM. *Scandinavian Journal of Forest Research*, 27:7, 692-699.

II Bohlin J., Bohlin I., Jonzén J., and Nilsson M. (2017). Mapping forest attributes using data from stereophotogrammetry of aerial images and field data from the national forest inventory. *Silva Fennica*, 51:2, article id 2021. 18 p.

III Bohlin J., Wallerman J., Olsson H., and Fransson J.E.S. (2012). Species-specific forest variable estimation using non-parametric modeling of multi-spectral photogrammetric point cloud data. In Proc: *International Archives of the Photogrammetry*, Volume XXXIX-B8, 2012 XXII ISPRS Congress, 25 August – 1 September 2012; Melbourne, Australia.

IV Bohlin J., Wallerman J., and Fransson J.E.S. (2016). Deciduous forest mapping using change detection of multi-temporal canopy height models from aerial images acquired at leaf-on and leaf-off conditions. *Scandinavian Journal of Forest Research*, 31:5, 517-525.

V Bohlin J., Wallerman J., and Fransson J.E.S. Assessment of tree species proportion from 3D image products (manuscript).

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

Abbreviations

3D	Three dimensional
a.g.l.	Above-ground level
ALS	Airborne laser scanning
CHM	Canopy height model
CIR	Colour infrared image
dbh	Diameter at breast height
DEM	Digital elevation model
DMC	Digital Mapping Camera (Zeiss Intergraph)
DSM	Digital surface model
FMPP	Forest management planning package
GPS	Global positioning system
GSD	Ground sampling distance
ITC	Individual tree crown approach
k-MSN	*k* most similar neighbour
Lidar	Light detection and ranging
NFI	National forest inventory
RMSE	Root mean square error

1 Introduction

Remotely sensed data for forestry applications are now increasingly available. Spectral data are collected in many forms and scales ranging from satellite images to airplanes to drones, with image resolution ranging from tens of meters to a few centimetres. Some data are collected on a daily basis and over the whole globe, while other data can be collected personally as needed. Structural or three dimensional (3D) data are gathered using laser, radar and optical images, allowing the forests to be measured in ways which were not possible before. On the ground, survey data can be collected using sensors on mobile platforms from cars to backpacks to handheld devices, and even harvesters can be used to collect forest information. This vast possibility of technology is now available to forestry.

Traditionally, forests have been managed in homogenous units or stands. Characteristics of forest stands are described as mean values for the whole stand, e.g., basal area weighted mean height (tree height), basal area weighted mean diameter (diameter), basal area, stem volume and tree species proportions. The stand is the unit for silvicultural treatments, like thinning and clear-cutting. Old information about the forest stands is replaced when a new inventory is conducted. Within stand variation or continuous variable characteristics are increasingly interesting aspects in modern forest management planning.

In Sweden, forest management planning commonly used forest stand maps with stand boundaries and forest variable estimates produced using a combination of manual photo-interpretation of aerial images viewed in stereo and supported by subjective measurements in the field (Åge, 1985; Magnusson et al., 2007; Ståhl, 1992). This method typically provides estimates with relative Root Mean Square Error (RMSE) of 10% (of the surveyed mean) for tree height and 15% - 25% for stem volume (Ståhl, 1992, 1988). Another common method was combining photo-interpreted stand boundaries with forest variable estimates produced using subjective field measurements alone, which generated standard errors of 15% - 25% for stem volume, and approximately 10% for tree height

(Ståhl, 1992). Tree species are commonly recorded as a proportion of stem volume at stand level. Aerial images are used operationally to manually assess tree species proportions using spectral as well as textural information (Åge, 1985).

Up until the late 1990s and early 2000s, all forests stands were inventoried and assessed with a field visit or at least visually inspected in a stereo photogrammetric work station. However, access to wall-to-wall remote sensing data and methods for estimating forest attributes by using field data from a sample of plots within the area of interest changed how data are collected in forest inventory.

The area-based approach is the most common modelling approach, where information or metrics from remotely sensed data are extracted from a sample of field surveyed areas, for example, circular plots, within the area of interest. The link between the surveyed forest variable of interest and the metrics from remote sensing can be modelled using various statistical methods. The remotely sensed data of the area of interest are then tessellated into units of the same area as the surveyed plots and the model are applied to produce wall-to-wall predictions of the surveyed forest variable of interest. Alternatively to area-based are object-based approaches, which for forest applications equals to individual trees and are commonly referred to as individual tree crown approach (ITC). Reviews of area- and ITC-based approaches and their use in forest applications can be found in Hyyppä et al. (2008) and McRoberts et al. (2010).

Early use of the area-based approach was the use of satellite image data and National Forest Inventory (NFI) plots for multi-source national forest inventory of Finland (Tomppo, 1993). In Sweden a similar forest map product was produced (Reese et al., 2003) for year 2000 based on Landsat Thematic Mapper data using the *k* nearest neighbour (*k*-NN) method, delivering a national 25 m cell resolution raster consisting of tree height, diameter, basal area, tree species-specific stem volume and age. The accuracy was not sufficient to be used by forest managers for silvicultural treatments at stand level, but useful for larger area analysis. Interest in model-based wall-to-wall estimates was created. The forest map was updated with data for year 2005 and 2010 and is planned to be continued.

In the late 1990s, apart from satellite-based inventories, lidar technology and airborne laser scanning (ALS) were applied in forest applications (Næsset, 1997a, 1997b; Nilsson, 1996). ALS generates 3D data by sending out a laser pulse, which, as it travels down towards the ground, generates echoes (returns) form the vegetation it interacts with and a last return as it reaches the ground. The returns are received by the system, and by using the time of flight and the known scan angle, a position (point) for each return can be calculated. As the position and orientation of the system is known using a global navigation satellite system and an inertial navigation system, the lidar point's coordinates are in a geographical coordinate system. A scanning lidar commonly emits hundreds of thousands of pules per second generating a point cloud from the area of interest. From the point cloud, various statistical measures (metrics) describing the forest at each inventory plot and wall-to-wall raster cell can be calculated and used in area-based approaches.

The first large area mapping using lidar and the area-based approach was done in Norway (Næsset, 2002b). ALS-based methods perform well enough for forest management planning, turning forest companies into users of ALS-based capture of forest data, primarily using area-based approaches (Magnussen and Boudewyn, 1998; McRoberts et al., 2010; Næsset, 2002b; Næsset et al., 2004). In the Nordic boreal forest, these methods deliver stand level estimation accuracies (in relative RMSE) typically in the range of 2.5% - 13.6% for tree height, 5.9% - 15.8% for diameter and 8.4% - 16.6% for stem volume (Næsset et al., 2004). Woods et al. (2011) showed plot level estimation accuracies of 5.2% - 8.2% for tree height, 14.3% - 18.2% for basal area and 13.9% - 20.5% for stem volume for different boreal forest types in Canada. Spectral data from aerial images have been used as an additional information source to estimate tree species-specific stem volume in ALS-based forest inventories using various frameworks (Hyyppä et al., 2008) such as non-parametric methods like *k* most similar neighbours (*k*-MSN) (Breidenbach et al., 2010; Packalén et al., 2009; Packalén and Maltamo, 2007). Due to high accuracy, ALS-based forest inventories are now common practice for forest companies in many countries (Vauhkonen et al., 2014; White et al., 2013). Also, many countries, such as Denmark, Finland, Netherland, Switzerland and Sweden, are performing or have performed national ALS surveys. In Denmark, the national ALS and NFI data have been used to estimate forest resources, reporting RMSEs of 42% for basal area and 46% for stem volume at plot level (Nord-Larsen and Schumacher, 2012). In Austria, low point density ALS data acquired for elevation mapping together with NFI data collected under operational conditions were used for wide-area stem volume estimation, resulting in standard deviation of 31.5% at plot level (Hollaus et al., 2009). For the Swedish national forest attribute map based on ALS data and NFI plots, stand level accuracies for 253 forest production stands in south and mid Sweden, RMSE ranged from 5.4% to 9.5% for tree height; from 8.7% to 13.1% for diameter; from 13.9% to 18.2% for basal area; and from 17.2% to 22.0% for stem volume (Nilsson et al., 2017).

The use of lidar technology opens up opportunities for other 3D technologies which can describe the forest canopy surface, since it provides an accurate model of the ground elevation (i.e., a digital elevation model or DEM). Stereo photogrammetry is one such technology, as it can deliver 3D data of the forest canopy generated from aerial images. Many countries have national image acquisition programs using large format digital mapping cameras with high repeat rates (e.g., in Sweden every 2 – 4 years over productive forest land). Image acquisition comes at lower cost then lidar, due to higher flight altitude and wider field of view of the sensor. Aerial images also include spectral information which are interesting for tree species discrimination. Aerial images have been used in forestry for a long time making it a familiar source of information to the end user.

Photogrammetry is the knowledge of measurement by images of light, which to a large part can be interpreted as measurement with cameras and is one of the oldest remote sensing techniques. Stereo photogrammetry is the technique where overlapping images are used to measure the distance to an object using triangulation. The development of digital images, image processing and computation power (computers) have greatly improved its use the last two decades.

In digital stereo photogrammetry, algorithms detect features in one image and match them to the corresponding feature found in overlapping images. For all features matched, their relative position to the camera is calculated using triangulation. Since the camera's position and orientation is known in a cartographic reference system, the position of the feature will be generated as a 3D point in the same coordinate system. When applied to all features in many overlapping images, a so called point cloud is generated.

Studies utilizing digital surface models (DSMs) derived by stereo photogrammetry report similar accuracies compared to those obtained with ALS when operated at the same flight altitude (Baltsavias, 1999). Næsset (2002a) used scanned analogue high-resolution (0.19 m pixel size) aerial images to derive 3D data using stereo photogrammetry. Ground elevation was assessed using manual photo-interpretation of the images viewed in stereo in a limited number of locations with visible ground, and then interpolated to full spatial cover. At the test site in Norway, tree height was estimated for forest stands using regression analysis with standard error ranging from 0.9 m to 2.1 m, which is similar to accuracy achieved using manual photo-interpretation. Nuske and Nieschulze (2004) reported 0.3 m systematic deviation and 1.4 m standard error when measuring stand heights of mature homogeneous beech forest in Germany from a DSM based on digitized stereoscopic images (0.44 m resolution). DSM data produced by stereo photogrammetry of UltraCamD imagery showed 0.8 m systematic deviation with 2.4 m standard error from measured upper layer tree heights of non-alpine forest in Austria (Hirschmugl et al., 2007). In two Canadian forested test sites, St-Onge et al. (2008) compared canopy height models (CHMs) assessed by ALS and photogrammetry using scanned analogue aerial images with 0.24 m pixel size (in both cases the ground elevation was determined by ALS), with the best correlation coefficient being 0.89. Plot metrics, such as height percentiles, derived from the two data sources using 20 m × 20 m windows were highly dependent showing correlation coefficients up to 0.95 (for the 95th height percentile).

Studying small-area estimation of forest attributes in Norway using NFI data and a photogrammetric DSM as auxiliary data, relative RMSE for biomass was 41.6% and 42.8% at plot-level for a linear mixed-effect model and a linear regression model, respectively (Breidenbach and Astrup, 2012). In one study from Finland, a canopy height model from aerial images was used together with field plots to estimate mean height, mean diameter, basal area and mean volume, resulting in relative RMSEs of 11.8%, 25.3%, 27.9%, 18.6% and 31.3%, respectively, at plot level (Vastaranta et al., 2013). In another study from Finland, Nurminen et al. (2013) used surface models from stereo photogrammetry reporting plot-level RMSEs of 6.7% 12.0% and 22.6% for height, diameter and stem volume, respectively, when using 80% forward overlap between images. A review article (White et al., 2013), compared lidar- and image-based point clouds for forest attribute estimation, concluding that the impact of the fact that image based point clouds only characterize the surface of the canopy needs to be studied more. Comparing lidar- and image-based metrics for survey plots, the similarity between metrics from the two data sources generally increased with increasing canopy cover (White et al., 2015). In a Norwegian study, lidar- and-image based estimates of forest characteristics were compared; for the image data, the best results were found using the smallest ground sampling distance (Gobakken et al., 2015). The article also gives a summary of the results from earlier lidar- and image-based methods for estimating forest attributes. For large area forest attribute mapping, aerial images and NFI plots were used resulting in RMSEs of 37.6%, 43.5% and 29.2% for basal area, timber volume and biomass, respectively, at plot level (Rahlf et al., 2017). In a study, Puliti et al. (2017) used Dirichlet regression to predict tree species-specific proportion and multiplied with the predicted total volume; they reported species-specific stem volume with relative RMSEs of 46.5%, 36.6%, and 84.9% for pine, spruce, and deciduous species, respectively, at plot level.

The introduction on digital stereo photogrammetry for forest data collection describes the research field until now, however, when this thesis project started in 2010, there was many topics to explore. Hence, the aims of this thesis.

2 Aim

The overall aim of the thesis is to assess the potential use of large format digital aerial images and stereo photogrammetry as a technology for collecting information for forest management planning.

Papers I-V:

I. Aims to investigate the possibilities of estimating forest variables with focus on tree height, basal area and stem volume, using 3D data from photogrammetric matching of Zeiss/Intergraph Digital Mapping Camera (DMC) images in combination with ALS DEM data. Performance of using image data of various resolutions and overlap is addressed using three different data sets.

II. Aims to evaluate the accuracy of forest attribute mapping using 3D data from standard aerial images from the national image acquisition program in Sweden, in combination with sample plot data from the NFI. Height, diameter, basal area and stem volume are mapped using the area-based approach. In addition, models for one sub-area are applied to other sub-areas to evaluate the effect of phenological variations (leaf-on/off) and model robustness for different geographical variations, like forest structure and composition.

III. Aims to investigate the possibilities of estimating species-specific (pine, spruce and deciduous trees) tree height, basal area and stem volume at stand level using spectral and 3D data from the DMC sensor in combination with ALS DEM data.

IV. Aims to evaluate the accuracy of estimating the proportion of deciduous stem volume using change detection between CHMs from leaf-on and leaf-off data sets in an area-based approach.

V. Aims to compare how different methods for colouring image point cloud data effects the estimation accuracy of tree species-specific proportions and stem volume estimation using standard image products. Also different spectral metrics and their importance for tree species estimation are compared.

3 Material

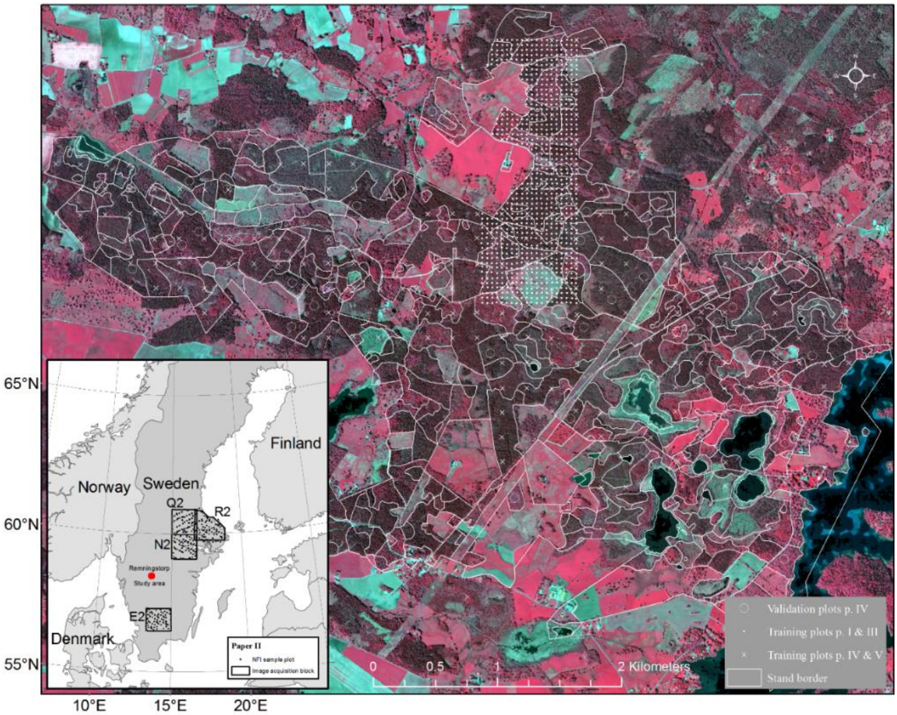

Figure 1. Orthomosaic (©Lantmäteriet) overlaid with the positions of field plots and an overview (inset) of the Remingingstorp study area's position showing the Nordic countries (©ESRI) and the sub-areas and NFI plots used in Paper II.

3.1 Study areas

For Papers I, III, IV and V, the study area is the Remningstorp forest estate, which is situated at 58°30' N, 13°40' E (Figure 1). The estate is privately owned, managed for timber production, and has relatively flat terrain. The forest is mainly dominated by Norway spruce (*Picea abies*), Scots pine (*Pinus sylvestris*), and birch species (*Betula* spp.).

The study in paper II was conducted in four image acquisition blocks (sub-areas) with the size of about 10 000 km^2 in southern (E2) and central (N2, Q2, R2) Sweden (Figure 1). In each sub-area, forests consist of all kind of developing stages and are mainly dominated by conifers (Scots pine and Norway spruce), but deciduous trees, especially birch, are also present. Forests are largely well-managed and owned by both forest companies and private land owners.

3.2 Field data

3.2.1 Training data

For the Remningstorp study area, field plots with 10 m radius were objectively surveyed using a regular quadratic grid design, with 40 m spacing between adjacent plots over the 1.0 km by 2.3 km central part of the estate (Papers I and III) or 200 m spacing for the entire estate (Papers IV and V). The origins of the grids were allocated randomly. Each plot was surveyed using the methods and state-estimating models of the Forest Management Planning Package (FMPP; Jonsson et al., 1993). For plots with mean tree height less than 4 m or mean stem diameter at breast height (dbh; i.e., 1.3 m above ground) less than 5 cm, height and species of all saplings and trees were recorded. For the remaining plots, calipering of all trees at breast height including only trees greater than 5 cm in stem diameter, and sub-sampling of trees to measure height and age, were performed. Heights of remaining callipered trees on the plots were estimated using models developed by Söderberg (1992) relating tree height to stem diameter. Plot location was measured using differential GPS producing sub-meter accuracy. Correction of the forest growth between the surveys and the date of aerial image acquisition was made by forecasting the forest state at each plot using single tree growth models (Söderberg, 1986).

In Paper II, plots from the Swedish NFI were used; the Swedish NFI surveys approximately 9500 sample plots in the field annually. Of these, 60% are permanent plots with a plot radius of 10 m that are revisited every five years while the remaining 40% are temporary plots with a 7 m radius. The NFI plots are positioned with GPS receivers giving a horizontal positional accuracy of about 5 m. These plots are organized into square or rectangular clusters consisting of 4, 6 or 8 plots total and with a distance between plots ranging from 300 m to 600 m. For Paper II, NFI plots were selected from the same year or

1–2 years before aerial image acquisition. NFI plots covered forests from different developing stages and tree species composition. Permanent and temporary plots on productive forest land with tree height over 3 meters were used. For these plots all trees were calipered. A summary of the training data is shown in Table 1.

Table 1. *Surveyed forest variables for the training plots in Papers I-V. Basal area weighted mean tree height (H), basal area weighted mean tree diameter (D), basal area (BA), mean stem volume (V), mean stem volume of pine (V_p), mean stem volume of spruce (V_s) and mean stem volume of deciduous (V_d)*

		Forest variable	Min	Mean	Max	Number of plots	Inventory method
Paper I		H (m)	2.9	18.4	30.3	344	FMPP
		BA (m^2 ha^{-1})	0.1	28.0	34.8		
		Vol (m^3 ha^{-1})	0.5	262.0	804.0		
Paper II	sub-area E2	H (m)	3.0	14.3	28.2	216	NFI
		D (cm)	1.3	18.2	43.4		
		BA (m^2 ha^{-1})	0.7	21.3	61.3		
		V (m^3 ha^{-1})	2.4	168.6	669.1		
	sub-area N2	H (m)	3.0	15.9	30.8	167	NFI
		D (cm)	3.5	21.0	42.8		
		BA (m^2 ha^{-1})	1.0	22.3	50.8		
		V (m^3 ha^{-1})	2.7	181.4	627.1		
	sub-area Q2	H (m)	3.1	15.0	28.4	223	NFI
		D (cm)	2.8	19.0	41.2		
		BA (m^2 ha^{-1})	2.7	22.0	50.5		
		V (m^3 ha^{-1})	6.6	174.9	547.9		
	sub-area R2	H (m)	3.0	17.0	29.8	233	NFI
		D (cm)	1.0	22.5	45.4		
		BA (m^2 ha^{-1})	0.1	23.8	59.8		
		V (m^3 ha^{-1})	0.5	207.9	701.5		
Paper III		H (m)	1.4	18.1	33.0	696	FMPP
		BA (m^2 ha^{-1})	0.0	26.1	62.2		
		V (m^3 ha^{-1})	0.0	249.0	829.0		
Paper IV		Decid. prop.	0.0	0.2	1.0	207	FMPP
Paper V		V (m^3 ha^{-1})	3.4	218.0	790.1	156	FMPP
		V_p (m^3 ha^{-1})	0.0	43.0	355.1		
		V_s (m^3 ha^{-1})	0.0	142.0	790.1		
		V_d (m^3 ha^{-1})	0.0	32.0	383.9		

3.2.2 Validation data

In Paper II, two independent data sets were used: i) forest company stands (company stands); ii) biotope protection stands (biotope stands) (see Table 2). Company stands represent typical forest stand used as planning and operational units in forestry, where data were collected using the methods and state-estimating models of the FMPP (Jonsson et al., 1993). Three to twelve circular sample plots having a radius between 5 m and 10 m were placed systematically in each stand depending on the size and heterogeneity of the stand. Biotope stands are areas created for conservation of biotopes and endangered species. The total stem volume was surveyed thoroughly since it was used for economic compensation to the land owners. Therefore, diameter measurement of all trees with dbh over 8 cm and about 100 height measurements per biotope stand were used to model the stem volume.

Table 2. *Summary of basal area weighted mean tree height (H), basal area weighted mean tree diameter (D), basal area (BA), mean stem volume (V) of the validation data for sub-areas E2, Q2 and R2 in Paper II*

	Company stands				Biotope stands			
Characteristic	Min	Max	Mean	Std	Min	Max	Mean	Std
E2, Company stands: n =25; Biotope stands: n=10								
H, m	-	-	-		-	-	-	-
D, cm	13	31	21.9	4.9	-	-	-	-
BA, $m^2\ ha^{-1}$	12.6	42.7	25.9	7.3	-	-	-	-
V, $m^3\ ha^{-1}$	91	380	211	75.6	144.4	357.0	262.5	66.3
Q2, n = 37/11								
H, m	10.5	24.8	17.8	3.7	-	-	-	-
D, cm	12.2	30.6	22.7	5.2	-	-	-	-
BA, $m^2\ ha^{-1}$	12.0	47.0	21.8	8.8	-	-	-	-
V, $m^3\ ha^{-1}$	65	540	219.0	106.4	179.3	508.8	341.0	95.1
R2, n =82/18								
H, m	9.1	24.9	18.9	3.7	-	-	-	-
D, cm	8.4	40.0	25.4	6.1	-	-	-	-
BA, $m^2\ ha^{-1}$	12.0	50.0	27.4	8.4	-	-	-	-
V, $m^3\ ha^{-1}$	61.0	509.0	243.3	101.3	254	481	349	67.0

Validation in Paper IV was done using an independent data set of 40 m radius plots placed within forest stands, and surveyed using the same method as the 10 m radius FMPP plots. A total of 47 validation plots were used where the tree height range was 6.8–31.4 m (mean 21.3 m), age 17–125 years (mean 57 years), proportion of deciduous stem volume 0.0–1.0 (mean 0.33) and the stem volume ranged from 20.1 to 555 $m^3\,ha^{-1}$ (mean 277 $m^3\,ha^{-1}$). For Papers I and III stand wise leave-one-out cross-validation was performed, i.e., all the field plots from one stand was omitted when training the model and the average of the omitted field plots values was used as validation data for the stand. In Paper V leave-one-out cross-validation on the training plots was performed.

3.3 Aerial images

For all papers, large frame aerial cameras for the national aerial image program have been used to acquire image data (Table 3). In Papers I, III and IV a DMC system was used, with standard acquisition settings of flight altitude 4800 m above ground level (a.g.l.) and 60% along-track image overlap and 30% across-track overlap (60/30% overlap). However, for Paper I, a 4800 m a.g.l. 80/30% overlap data set and a 1200 m a.g.l. 80/60% overlap data set were also collected. The DMC system consists of four panchromatic and four spectral camera heads. The four panchromatic images are stitched into one image and merged with the spectral images to create one pan-sharpened virtual image with 7680×13824 pixels (Hinz et al., 2001). The ground sampling distance (GSD) for the 4800 m image block is approximately 0.48 m and 0.12 m for the 1200 m block. For Papers II and V, the Vexcel (Microsoft) UltraCam Xp and Eagle camera systems were used flying at 2800 and 3700 m a.g.l., respectively, generating images with a GSD of 0.25 m and with a 60/30% overlap. The UltraCam systems also consist of four spectral camera heads and multiple panchromatic camera heads where the separate images are stitched into one image. For all papers, the images were block triangulated using bundle adjustment and radiometrically corrected by Lantmäteriet, as part of their operational aerial image production. The radiometric correction was conducted using a model based approach, which included correction of haze, atmospheric effects, hotspots and an adjustment of the final colourtone (Wiechert and Gruber, 2011), resulting in pan-sharpened Colour Infrared (CIR) images (Green, Red, Infrared) with an 8-bit radiometric resolution, used for Papers I, II, IV and V. For Paper III, a lower level image product (LR4) was used where only the stitching of the panchromatic images and no pan-sharpening or radiometric correction was done. Aerial acquisitions were made both in summer leaf-on season as well as spring leaf-off season (Papers II and IV).

Table 3. *Summary of image data sets used*

Paper	Sensor	Overlap forward/side (%)	Ground sampling distance (m)	Spectral product	Season
I	DMC	80/30, 60/30, 80/60	0.48 0.12	8-bit CIR	leaf-on
II	UltraCam	60/30	0.25	8-bit CIR	leaf-on, leaf-off
III	DMC	60/30	0.48	12-bit LR4	leaf-on
IV	DMC	60/30	0.48	8-bit CIR	leaf-on, leaf-off
V	UltraCam	60/30	0.25	8-bit CIR	leaf-on, leaf-off

4 Methods

4.1 Stereo photogrammetry

In Papers I and III, stereo photogrammetry was performed using the Match-T DSM software version 5.3.1 (Anon., 2011) to produce point cloud data for each data set. This was done by sequential multi-matching (Lemaire, 2008), where both least squares and feature-based matching were combined. A number of different settings were applied to evaluate their effects on the generated point cloud and DSM. In the end, the parameters that produced the DSM with the highest visible dynamic range were selected, which excluded filtering of the point cloud data. In Papers II, IV and V, stereo photogrammetric processing of the images to produce point cloud data was done using the SURE software (Rothermel et al., 2012) which generates a height value for each pixel, using a modified semi-global matching algorithm (Hirschmüller, 2008). Software setting AERIAL6030 (pre-defined settings optimized for aerial surveys with 60/30% overlap) was used to define parameters for point cloud generation. Finally, the point cloud height values were transformed from height above mean sea level to height above ground level by subtracting the height of the ground with an elevation model originated from ALS.

4.2 Metrics

For the area-based approach, metrics describing the forest at the training plots and for raster cells over the area of interest are needed. Metrics were derived from the point cloud data sets for each field plot. For the modelling, metrics describing canopy height were derived as percentiles corresponding to, for example, the 10^{th}, 20^{th}, …, 90^{th}, 99^{th} and 100^{th} quantiles of the point height distribution. Two types of canopy density metrics were derived. First, the proportions of points over, for example, 20%, 30%, 40%, and 50% of the maximum height (i.e., 95th or 100th percentile), and second, the proportions of points over fixed heights of 2 m, 3 m, 4 m, and 5 m, were calculated for each field plot. Different moments of the point height distribution, such as mean, variance and skewness have also been calculated. These metrics were generated using Fusion (McGaughey, 2016). Aerial stereo photogrammetry produces point cloud data based only on the canopy surface that is visible from above. In contrast to lidar, which penetrates canopy and captures the complete height distribution, the density metrics from stereo photogrammetry are not expected to be as explanatory for forest variable estimation as their lidar counterparts. Therefore, height-based texture metrics were investigated as a complement. Texture metrics (Haralick et al., 1973) such as angular second moment; contrast; entropy; homogeneity; inverse difference moment; and maximum probability were evaluated in Paper I. For Papers II and V a CHM was generated, with 0.5 m cell size, assigning the maximum height to each raster cell. Metrics describing the surface of that CHM were calculated, such as the mean of canopy height; slope; aspect; surface ruggedness; and surface roughness (Hijmans et al., 2016). These metrics were also calculated with all no-data pixels (i.e., occluded areas) set to zero instead of being ignored in the calculation. Also, with the aim of describing forest density, a filter approach was used where a 3 by 3 pixel window identified the centre cell as local maxima if the eight neighbours had a lower or equal height value. For each training plot, the number of local maxima and sum of squared heights of the local maxima were calculated from the image based CHM and a CHM smoothed using a 3 by 3 pixel mean filter. In Paper V, using the planar position (2D) of the local maximum, two spatial descriptive statistics have been applied: i) spatial dispersion was calculated as the average distance between nearest neighbours (Clark and Evans, 1954), and ii) deviations from spatial homogeneity using Ripley’s K function (Ripley, 1976). In Paper IV, metrics describing the change in the canopy height between two seasons was used. A binary raster was created where cells where classified as changed if the change in height value between seasons was above a given threshold. Different thresholds based on relative heights were used and investigated. A summary of metrics and models for all papers is in shown Table 4.

4.3 Modelling

Throughout all papers the area-based approach has been used to predict the variables of interest. In Papers I, II, IV and V linear regression were used to model tree height, diameter, basal area and stem volume. Independent variables (metrics) were selected based on regression model fit statistics and studies of residual plots. Bias correction was carried out for predictions with logarithmic or square root transformation of the variable of interest.

In Paper III, as a pre-modelling step, each point in the cloud was classified as either pine, spruce or deciduous. This was performed by supervised classification with the spectral information using plots with uniform species composition, defined as plots where more than 95% of the field surveyed volume consisted of pine, spruce or deciduous trees (40, 351 and 18 plots, respectively) as training data. Species classification of the point cloud was made using quadratic discriminant analysis with equal prior probabilities. The forest variables of interest: tree height, basal area, total stem volume, pine stem volume, spruce stem volume and deciduous stem volume were estimated using *k*-MSN, with $k = 1$. Stem volume and basal area were logarithmically transformed in order to achieve linear relationships in the canonical correlation transformation. Estimation was done using the YaImpute library (Crookston and Finley, 2008) in the R statistical software package (R Core Team, 2015) and resulted in raster data sets for the variables of interest.

For estimating tree species-specific proportions a Random Forest approach was used (Papers IV and V). This, since the variable (i.e., species proportion) is a fraction, that is, continuous values within the finite interval [0,1], and shows non-linear dependencies to the metrics. A parametric method such as ordinary linear regression is not directly applicable due to the non-normal error distribution and lack of linearity. Thus, models relating the addressed proportions to the calculated metrics were developed using the non-parametric method Random Forest (Breiman, 2001, 1996) implemented in the R package randomForest (Liaw and Wiener, 2002; R Core Team, 2015). In short, it combines the ideas of regression trees and bootstrap aggregating (“bagging” (Breiman, 1996)) to fit and evaluate a large number of regression trees (a “forest”). Each tree is fitted using a random sample of the training data, and each node of the tree is defined by the best splitting variable out of a small random selection of the independent variables (i.e., the metrics). Error and variable importance are assessed using the training data left out (out-of-bag data). Given the forest of regression trees, final estimation is made using majority votes.

4.4 Validation

Validation has been done using leave-one-out cross-validation or validation using an independent data set. When prediction has been done to raster cells, the cell size was chosen to be close to that of the plot area, except in Paper II, where a smaller cell size was used. This was to resemble the data of the national forest attribute map, an already existing data set generated from lidar. For stand level accuracy, raster cells of the predicted variable were overlaid with stand borders and intersecting cells were aggregated and assessed against surveyed stand means. Performance was reported in RMSE in absolute terms and RMSE in percent of surveyed mean as well as bias in absolute terms and bias in percent of surveyed mean.

Table 4. *Summary of materials and methods for all papers. Basal area weighted mean tree height (H), basal area weighted mean tree diameter (D), basal area (BA), mean stem volume (V), mean stem volume of pine (V_p), mean stem volume of spruce (V_s) and mean stem volume of deciduous (V_d)*

Paper	Inventory method	Number of plots	Modelling approach	Variables of interest	Metrics
I	FMPP	344	linear regression	H, BA, V	height, density, texture
II	NFI	216, 167, 223, 233	linear regression	H, D, BA, V	height, density, CHM, local maximum
III	FMPP	696	*k*-MSN	H, BA, V, V_p, V_s, V_d	height, density, spectral
IV	FMPP	207	Random Forest	Deciduous proportion	height
V	FMPP	156	linear regression, Random Forest	V, V_p, V_s, V_d	height, density, CHM, local maximum, spectral

5 Results and discussion

5.1 Predicting non species-specific forest attributes

In Papers I, II, III and V non-species specific forest attributes were predicted. A summary of the results are presented in Table 5, together with results from other referenced studies.

Paper I showed that 3D data from the standard aerial image acquisition carried out by Lantmäteriet could be used to accurately estimate tree height, basal area and stem volume for forest management planning. At stand level, the best results in terms of RMSE using these image data were 8.8% for tree height, 14.9% for basal area and 13.1% for stem volume. Also, it was shown that increasing the image overlap and decreasing the ground sampling distance did not improve estimation results. In Paper III, very similar results (Table 5) were reported using a different method and data set, but at the same test site. Other studies have confirmed the performance and usability. From Finland, Nurminen et al. (2013), confirmed the results that the increase in forward image overlap, from 60% to 80%, did not clearly improve estimation accuracy and contributed with new knowledge that estimation accuracy was not impacted by the plots' off-nadir angle. Vastaranta et al. (2013) compared image and lidar based metrics and predicted forest attributes, concluding that performance was similar in single-layered even-aged stands. They argued that for other types of forests, image based predictions need to be studied further. An early review article from Canada continued on this previous work by covering the differences between image and lidar point clouds and their usability in forest inventory (White et al., 2013). This was followed up by a thorough study on the differences between metrics derived from image and lidar point clouds (White et al., 2015), reporting the largest differences in metrics for low percentiles and sparse forests, but similar accuracies in general when estimating forest variables using an area-based approach. Gobakken et al. (2015) concluded that image-based point clouds performed similarly compared to lidar for six forest variables in different forest strata in Norway, but that more research was needed before it could be used in large-scale forest operational use. There are some small differences in the accuracies within each variable presented in Table 5, these are probably because of differences in: forest type (e.g., distribution and mean of variable of interest); number and size of field plots, method used for modelling; validation method (e.g., n fold in cross-validation) and the size of validation stands.

Table 5. *Estimation accuracy of non-species specific forest variables in terms of relative RMSE. Basal area weighted mean tree height (H), basal area weighted mean tree diameter (D), basal area (BA), mean stem volume (V)*

	Plot level				Stand level			
Paper	H (%)	D (%)	BA (%)	V (%)	H (%)	D (%)	BA (%)	V (%)
I					8.8		14.9	13.1
II	9.5 –13.5	16.6 – 19.7	26.0 – 29.8	28.8 – 32.9	7.7 – 10.5	12.0 – 17.8	17.7 – 21.1	21.8 – 22.8
III					7.5		11.4	13.2
IV	-	-	-	-	-	-	-	-
V				36.0 – 36.7				
Vastaranta et al. (2013)	11.2	21.7	23.6	24.5				
Nurminen et al. (2013)	7.5	12.0		22.6				
White et al. (2015)	14		37.7	36.9				
Gobakken et al. (2015)	6.6 – 10.2	12.6 – 18.7	11.8 – 18.3	12.0 – 21.7	6.8 – 7.7	8.6 – 14.1	10.5 – 15.3	13.1 – 17.4
Rahlf et al. (2017)			37.7	43.5				

In Paper II, the use of image based point clouds was scaled-up to larger areas with varying conditions. Using NFI plots for training, results showed higher RMSEs (ranging from 7.7% to 10.5% for tree height; 12.0% to 17.8% for diameter; 17.7% to 21.1% for basal area; and 22.0% to 22.7% for stem volume, at stand level) than for dedicated 3D remote-sensing-based forest inventories, which often use various sampling designs for allocation training plots. However, the results were similar to the Swedish National Forest attribute map (RMSEs ranging from 5.4% to 9.5% for tree height; 8.7% to 13.1% for diameter; 13.9% to 18.2% for basal area; and 17.2% to 22.0% for stem volume), which is based on lidar and NFI plots (Nilsson et al., 2017). In a similar study from Norway, Rahlf et al. (2017) used image data and NFI plots, which resulted in RMSEs of 37.7% and 43.5% for basal area and timber volume, respectively, at plot level. Plot level RMSE in Paper II was 26.0% to 29.8% for basal area and 28.8% to 32.9% for stem volume.

Results also showed that the accuracies between forest types clearly differs for both image- and lidar-based methods, but between methods the difference in accuracy is small (Figure 2). This agrees with a study from Canada (Pitt et al., 2014), which observed other forest types, and concluded that accuracy varied between strata, but was similar between image and lidar point clouds. Similar results were presented in Gobakken et al. (2015), where for three different strata according to age class and site quality, lidar performed slightly better except for young and mature forest on poor sites where tree height was estimated slightly better using images.

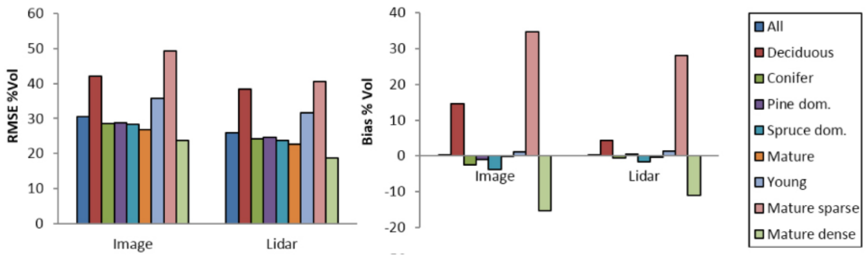

Figure 2. Relative RMSE and bias for image- and lidar-based predictions of stem volume in different forest types (from Paper II) at plot level.

Paper II also concluded that image data from leaf-off season should be avoided since the height distribution of the point cloud is affected for the leaf-off deciduous trees, resulting in underestimation and poor accuracy.

In Papers I, II, III and V, total stem volume was predicted and the results are in line with other studies (Table 5). Predictions of basal area and stem volume using image-based point clouds are similar, but not as accurate as for lidar-based predictions (Gobakken et al., 2015; Vastaranta et al., 2013; White et al., 2015; Yu et al., 2015). This is probably because of the difficulty of describing the forest density using images which only capture the top of the canopy, explaining the large bias for both sparse and dense mature forest (Figure 2). Estimating canopy cover using image-based point clouds, Melin et al. (2017) reported that 3D canopy density was challenging to describe using image-based point clouds. Already in Paper I, this was addressed by complementing the commonly used lidar density metrics (i.e., proportion of points over specific thresholds) with texture metrics (Haralick et al., 1973) derived from the CHM. The conclusion was that the texture metrics did not really improve the estimation accuracy, but were exchangeable to image based common density metrics. In Papers II and V, surface-describing metrics, such as slope and roughness, were derived from the CHM and used for prediction. Roughness was used for modelling total stem volume for all image data sets in Paper V. Setting the NoData cells in the CHM to zero resulted in the occluded areas being gaps instead (Figure 3), which could create bias. However, ignoring the NoData in the calculations of metrics also creates bias. As an example: calculating the proportion of points over 2 m from the lidar points in Figure 3a would result in a value of 65%. Doing the same for the image-based points would result in a value of 100%. However, doing the same on the CHM where NoData was set to zero would result in a value of 61%.

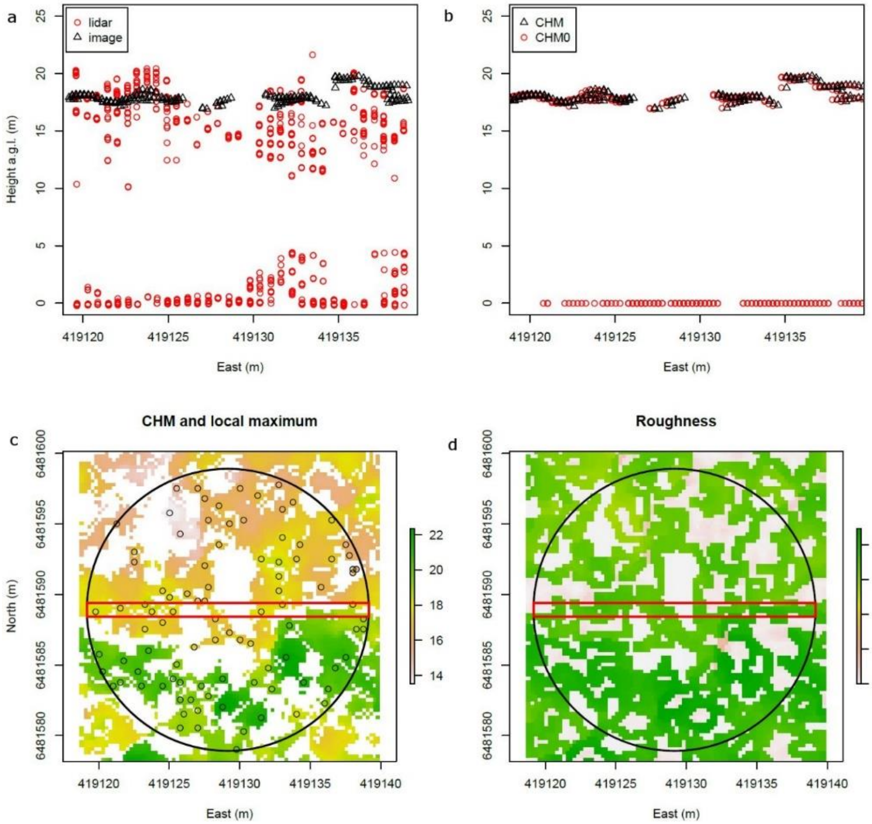

Figure 3. Examples of (a) lidar and image point clouds for a 1 m transect, (b) CHM with NoData and CHM with NoData set to zero for a 1 m transect (CHM0), (c) CHM with local maxima and transect in red, and (d) surface roughness.

In Paper V, local maxima of the CHM (Figure 3) were used to calculate the sum of squared heights at the plot. This was the single best metric for modelling total stem volume for the image-based products and was used for all four data sets. The two spatial descriptive statistics, spatial dispersion (Clark and Evans, 1954) and Ripley's K function (Ripley, 1976), did not improve stem volume prediction. However, it would be of interest to test application of a marked spatial point process (i.e., using the 3D position of the points).

5.2 Predicting tree species-specific attributes

In Paper III, species-specific stem volume was estimated using the *k*-MSN method resulting in absolute RMSEs of 25.5 m^3 ha^{-1}, 46.1 m^3 ha^{-1} and 10.6 m^3 ha^{-1} for pine, spruce and deciduous, respectively, at stand level. The species-specific stem volume estimates showed marginally lower absolute accuracies compared to Packalén and Maltamo (2007), which combined lidar and images, resulting in better absolute RMSE for spruce (27.0 $m^3 ha^{-1}$), but more similar for pine and deciduous stem volume with 27.7 $m^3 ha^{-1}$ and 13.7 $m^3 ha^{-1}$, respectively, at stand level. Measured in relative terms, the results of Paper III -- RMSEs of 90.6% , 26.4% and 72.6% -- are higher compared to their RMSE results of 28.0%, 32.6% and 62.3% for pine, spruce and deciduous stem volume, respectively (Packalén and Maltamo, 2007). These differences are probably due to the large differences in surveyed mean values. Furthermore, Paper III was carried out using a simplified framework compared to the thorough study performed by Packalén et al. (2009). In Paper III, estimation was performed using imputation as a mean to preserve the natural dependencies between estimated variables; *k*-MSN was applied using $k = 1$ rather than a larger value of *k*, which is expected to produce more accurate results. Using stereo photogrammetry of aerial images, Puliti et al. (2017), reported RMSEs of 43.3%, 35.0% and 80.1% for pine, spruce and deciduous stem volume, respectively, at stand level which is better than in Paper III. An extensive transformation of predictor variables and an exhaustive variable selection method using best subset regression was used Puliti et al. (2017), aiming to find best performing variables, creating multiple-linear regression models for total stem volume and modelling of tree species proportions with Dirichlet regression.

In Paper V, absolute RMSE for the species proportions were 24%, 23% and 20% for pine, spruce and deciduous, respectively. However, for the species-specific stem volume at plot level, the RMSE in percent of surveyed mean was 129%, 60% and 118% for pine, spruce and deciduous, respectively. The colouring method of the point cloud and using more complex spectral metrics showed little improvement in estimating tree species-specific proportions. In general combining spectral and spatial information from two seasons improved the species estimation, especially for the deciduous proportion, but also for the coniferous proportions.

Species-specific forest variables are important for forest management and therefore they have been studied over the years (Breidenbach et al., 2010; Maltamo et al., 2015; Packalén et al., 2009; Packalén and Maltamo, 2007; Puliti et al., 2017), but RMSEs in percent of surveyed mean is very dependent on the mean stem volume of the tree species, making comparison difficult to perform. Another problem with reporting RMSE is that it does not describe the distribution of the error for the range of the species-specific stem volume or proportion of volume estimation. In Paper V, when comparing the histograms of the field surveyed and estimated species proportions it is clear that species-pure plots are underestimated and mixed plots are overestimated. Similar results can be seen in Puliti et al. (2017), however, the same errors at the ends of the species-specific distribution are not visible in the results by Packalén and Maltamo (2007).

To improve tree species classification, research has been aimed at calibrating sensors and performing radiometric correction of aerial images (Honkavaara et al., 2009; Korpela et al., 2011). Nevertheless, the proximity effects in mixed stands was found to influence the mean reflectance by 1%–17% in the visible bands and up to 33% in the near-infrared (NIR) band, adding substantial classification errors (Korpela et al., 2011). When classifying species of individual trees, using the directional reflectance effect in multi-image data, and the use of atmospherically corrected reflectance images from the Leica ADS40 narrow-banded camera did not improve the classification compared to using spectral averages (Korpela et al., 2014). The properties of the trees explained as much as 58%–70% of the variance in NIR reflectance, while directional reflectance anisotropy explained only 4%–14%. They concluded that directional reflectance anisotropy between species does not differ enough to improve tree species classification, even though the images have been accurately reflectance calibrated. This partly explains the results in Paper V, that selecting the right method of colorization or using more complex spectral metrics does not improve species discrimination compared to using simple averages of spectral values.

In Paper IV, 3D information from standard aerial images of the forest canopy acquired at different seasons (leaf-on and leaf-off) was used to map the proportion of deciduous stem volume with good results. The non-parametric Random Forest approach was used to estimate the proportion of deciduous stem volume and the accuracy assessment at stand level showed an absolute RMSE and bias of 18% and −6%, respectively (in the best case). Classifying the estimates in four equally wide classes resulted in an overall accuracy of 83% (kappa value = 0.68). To the best of my knowledge, no other study have used 3D data from leaf-on and leaf-off images to estimate or map deciduous trees. However, using leaf-off ALS data to classify tree species composition at field plots into coniferous or deciduous dominated forest resulted in 91% overall accuracy (Villikka et al., 2012), which is directly comparable with the 89% overall accuracy obtained by the proposed method when using the same class boundaries. The result of 18% absolute RMSE corresponds with the 20% to 25% RMSE for deciduous proportion at plot level presented in Paper V. However, in Paper IV no spectral information was used, whereas spectral information was used in Paper V.

6 Conclusions

Aerial images and stereo photogrammetry utilized in an area-based approach for forest variable estimation of non-species specific forest attributes performs better than traditional inventories based on either photo-interpretation or subjective field inventory. Compared to lidar-based forest inventories, which are commonly used today, similar results are achieved. Therefore, concluding that aerial images and stereo photogrammetry produce an acceptable level of accuracy for use as a data source for forest management planning and to a much lower cost than ALS. However, very sparse forests, deciduous forests and mature forests have larger estimation errors. Nevertheless, from a forest management perspective, forest information can be collected at very low costs and with high spatial and temporal resolution. The 12 to 18 m spatial resolution used here is enough to describe within stand variations of the forest attribute. The use of aerial images from national image acquisition programs guarantee continuous flow of image data with a high temporal resolution, e.g., 2-4 years for most of Sweden. Also, Lantmäteriet now produces a coloured DSM from their images using stereo photogrammetry, making the technology highly available. Today, the research field of predicting tree height, diameter, basal area and stem volume using the area approach and stereo photogrammetry is thoroughly explored, except maybe for improving metrics describing forest density.

Predicting tree species-specific forest variables using aerial images with an area-based approach is still challenging. Using default colouring of the point cloud and averages of spectral values within plots when predicting species-specific variables performs similarly to other methods. From the perspective of a forest manager, the underestimation of species-pure plots and overestimation of mixed plots is undesirable, as forest managers strive for species-pure stands using silivcultural treatments.

7 Future outlook

Further research is needed to improve the species-specific estimates at the extremes of the range of the species distribution. Possible paths towards doing this would be to use sub-plot level information and narrower spectral bands. However, with new, higher resolution mapping cameras, increased spatial resolution is possible which will make the patterns of branches and other structural information available for use in tree species classification.

Stereo photogrammetry of aerial images from national acquisition programs has the advantage of not only giving new data often, but also that those programs have been acquiring national image data sets for decades. With the digitisation of those data sets, important forest variables like growth development and site index could be estimated. Time series of aerial images could possibly be used to detect changes in the forest landscape, both man-made and natural disturbances. Information on site index combined with mapping of changes could improve growth models and forecasts of forest variables between mapping campaigns.

The vast amount of available remotely sensed data together with an open data policy of governmental organisations will benefit the forest owners, in particular private forest owners with small estates. As an example, the next version of the Swedish National Forest attribute map will be made based on the digital surface model generated from aerial images from the Lantmäteriet together with NFI plot data.

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1. Besson, L. (1988) *Le grand blue*, Garmont, France.