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Forest resource mapping using 3D remote sensing: Combining national forest inventory data and digital aerial photogrammetry

Kartlegging av skogressurser med 3D fjernmåling: Kombinering av data fra landskogtakseringen og fotogrammetri med flybilder

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Johannes Rahlf

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PhD supervisors

Professor Erik Næsset
Department of Ecology and Natural Resource Management
Norwegian University of Life Sciences
Postboks 5003, 1432 Ås, Norway

Dr. Svein Solberg, Research Professor
National Forest Inventory
Division for Forestry and Forest Resources
Norwegian Institute of Bioeconomy Research
Postboks 115, 1432 Ås, Norway

Dr. Johannes Breidenbach, Research Professor
National Forest Inventory
Division for Forestry and Forest Resources
Norwegian Institute of Bioeconomy Research
Postboks 115, 1432 Ås, Norway

Dr. Rasmus Astrup, Head of Research
Division for Forestry and Forest Resources
Norwegian Institute of Bioeconomy Research
Postboks 115, 1432 Ås, Norway

Evaluation committee

Professor Håkan Olsson
Division of Forest Remote Sensing
Department of Forest Resource Management
Swedish University of Agricultural Sciences
90183 Umeå, Sweden

Associate Professor L. Monika Moskal
School of Environmental and Forest Sciences
College of the Environment
University of Washington
Box 352100, Seattle, WA, 98115-2100, USA

Professor Terje Gobakken
Department of Ecology and Natural Resource Management
Norwegian University of Life Sciences
Postboks 5003, 1432 Ås, Norway

Preface

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Ås, December 2016

Johannes Rahlf

Contents

List of papers

Paper I

Rahlf, J., Breidenbach, J., Solberg, S., Næsset, E. & Astrup, R. (2014). Comparison of Four Types of 3D Data for Timber Volume Estimation. Remote Sensing of Environment, 155, 325–33.

Paper II

Rahlf, J., Breidenbach, J., Solberg, S. & Astrup, R. (2015). Forest Parameter Prediction Using an Image-Based Point Cloud: A Comparison of Semi-ITC with ABA. Forests, 6(11), 4059–71.

Paper III

Rahlf, J., Breidenbach, J., Solberg, S., Næsset, E. & Astrup, R. (2017). Digital Aerial Photogrammetry and NFI Data for a Large-area Forest Inventory. Forestry, in review.

Paper IV

Astrup, R., Rahlf, J., Bjørkelo, K., Debella-Gilo, M., Gjertsen, A.K. & Breidenbach, J. (2017). Forest information at multiple scales: Development, evaluation and application of the Norwegian Forest Resources Map. Manuscript.

Abstract

National forest inventories (NFI) provide information at national and regional scales. At smaller scales, however, often too few sample plots are available for accurate estimates. The increasing availability of large area 3D remote sensing data gives the opportunity to create wall-to-wall forest maps based on reference data from NFIs. Digital aerial photogrammetry (DAP) allows the creation of detailed 3D information from overlapping digital aerial images over large areas at low costs. The objective of this thesis was to assess the use of DAP in combination with NFI data.

In the first study, DAP was compared to other 3D remote sensing techniques, namely airborne laser scanning (ALS), satellite interferometric synthetic aperture radar (InSAR), and satellite radargrammetry based on the accuracies of timber volume models. All models had good model fits. It could be shown that at stand level predictions with ALS were slightly more accurate than predictions based on DAP, which were more accurate than predictions using satellite SAR data. The second study analyzed the use of DAP in a semi individual tree crown (semi-ITC) approach for modeling various forest parameters. At plot level, timber volume predictions of the semi-ITC approach had accuracies and systematic errors similar to the area based approach (ABA). Multivariate kNN models were slightly more accurate with the semi-ITC approach than with the ABA, but had larger systematic errors. In the third study a timber volume model was fit for a large study area and the influence of large-area factors on the accuracy of timber volume predictions was investigated. The obtained accuracy of the predictions was lower than reported for earlier studies conducted on smaller study areas. The solar incidence angle relative to the terrain had a significant influence on the model. Finally, the use of DAP for an operational forest resource map was analyzed. Various forest parameters were mapped for a large area using 3D and spectral information from DAP combined with NFI data. Forest parameter models were less accurate than reported for earlier studies on small areas, but stand volume estimates were in line with existing forest management inventories. Model-assisted estimates at regional and municipality level were more precise than estimates based on NFI sample plots alone. The update of a forest mask produced a highly accurate classification of forest and non-forest. A tree species classification showed low accuracies, which, however did not differ greatly from accuracies reported in earlier studies.

In conclusion, the combination of DAP with NFI data allows cost-efficient mapping of forest parameters over large areas with high detail. Such maps showed to improve the estimates of the Norwegian NFI at various scales. Stand-level estimates of large mapping applications might be sufficiently accurate to be used in forest management planning or in the design of forest management inventories.

1 Introduction

Forest inventories provide information on forests on various scales. The range of variables reported by forest inventories varies, but typically includes the forested area, tree species, timber volume, and age. In sampling based forest inventories, measurements are taken only on parts of the area of interest (AOI). From this sample the forest parameters of the whole population (i.e. the AOI) can be estimated. In addition, remote sensing is often used in the design phase (e.g. in stratification) and in the estimation phase as auxiliary data.

In many developed countries, two different forest inventory systems provide statistics on different spatial scales. National forest inventories (NFI) provide information on forest resources on national and regional level. Such statistics are the basis for forest policies and national forest programs, but also serve a variety of other uses such as international reporting and the monitoring of ecosystem services (Tomppo et al. 2010). As in many developed countries, the Norwegian NFI consists of a network of permanent sample plots. The Norwegian NFI traditionally provides estimates of forest resources for the whole of Norway and for counties (Tomter et al. 2010). However, on smaller scales the number of NFI plots is usually too small to assure accurate estimates. Therefore, estimates for municipalities, estates, or single stands cannot be derived from NFI data alone.

At local scales, forest information is typically provided by forest management inventories (FMI). FMIs aim to provide information on individual forest stands which allow strategic and tactical planning of forest properties. Until the 1970s a common practice to obtain stand information in FMIs in Norway were stand-wise field inventories. those required field visits to every stand, where stand parameters were measured or visually assessed. Nowadays, most FMIs combine field surveys with remote sensing, particularly airborne laser scanning (ALS), which allows estimation of stand parameters (Næsset 2014). Remote sensing data are linked to the sample plot measurements by statistical modeling. These linking models are then used to predict forest parameters for the AOI, creating wall-to-wall covering forest maps. Forest maps give an overview of the forest resources and can therefore be used to support tactical planning of forest operations. The main purpose of prediction maps, however, is serve as basis for estimation of stand level means and totals.

In recent years, increasingly more three-dimensional (3D) remote sensing data have become available over large areas, which have proven highly suitable for forestry applications. These data give now the opportunity to create forest maps by combining NFI sample plots with remote sensing. Due to the large spatial extent, sufficient numbers of NFI sample plots intersect with the remote sensing data. This allows fitting of linking models and thus the construction of forest resource maps. Depending on the auxiliary remote sensing data, such maps may have great spatial detail and high accuracy and may be used to estimate forest parameters in small areas, such as municipalities, estates or even forest stands.

ALS is a popular source of 3D data for forestry applications and has been thoroughly studied for over two decades. Its advantage over most other remote sensing technologies is the ability to provide information on the terrain below the tree canopy and to characterize structure of the canopy (Vauhkonen et al. 2014). In several countries, such as Norway, Sweden, and Finland, ALS is an operational method in FMIs (Næsset 2014). With increasingly more area covered by ALS and country-wide acquisitions, often with the purpose of acquiring detailed terrain information, ALS has also become a source of data for large-area forest resource mapping (e.g. Nord-Larsen & Schumacher 2012, Nilsson et al. 2016).

A genuine source of large-area information is satellite imagery. An advancing technique for acquiring 3D data from satellites is synthetic aperture radar (SAR), which uses microwaves to illuminate the surface. Among the processing methods to derive 3D information from satellite SAR are interferometric SAR (InSAR) and radargrammetry, which have been used to model key forest parameters such as height and biomass (Solberg et al. 2013, Askne & Santoro 2015, Soja et al. 2015*b*,*a*, Solberg, Riegler & Nonin 2015). With upcoming satellite missions, an increase in the use of space-borne InSAR for forestry applications can be expected.

Another promising technique of acquiring 3D data is digital aerial photogrammetry (DAP). While photogrammetry has been used in forest mensuration for over a century (Müller 1931), only with its full digitalization and the recent developments in hardware and processing algorithms is it now possible to automatically obtain 3D information from aerial photographs over large areas with point densities and accuracies similar to ALS (Leberl et al. 2010). An early study processing DAP data similar to ALS data was conducted by Næsset (2002), who showed the possibilities of using DAP in forest parameter mapping. Even though DAP is not able to depict the structure of forest canopies as well as ALS, Bohlin et al. (2012) and Nurminen et al. (2013) compared forest parameter models using DAP and ALS, and obtained similar accuracies on stand-level. A large advantage of DAP is that 3D data can be obtained from aerial images acquired with the aim of orthophoto generation, which makes DAP a promising tool for large-area forestry applications. An example of a large-area application is the creation of country-wide 3D data in Switzerland (Ginzler & Hobi 2015) which were then used to map forest area by Waser et al. (2015). However, contrary to ALS, which has been thoroughly investigated, studies on the use of DAP as a source for auxiliary data in forest inventories are yet few, but rapidly increasing.

In countries where survey programs are in place, which aim to collect aerial images for orthophoto generation at regular intervals, DAP allows inexpensive generation of 3D data over large areas. Together with its high spatial resolution DAP is therefore an ideal data source for large-area forest mapping using NFI sample plots as reference data for forest parameter modeling. However, since both data are acquired for different purposes, and DAP is still a relatively new data source in forestry applications, little is known about possibilities and accuracies when combining the DAP and NFI data for forest resource mapping over large areas.

2 Objectives

This thesis addresses the synergistic integration of NFIs and forest resource mapping using 3D remote sensing. The main objective of the thesis was to assess the use of DAP combined with NFI data for mapping of forest resources. In particular, I wanted to (1) bring DAP into perspective with other 3D remote sensing techniques based on model accuracies for forest attribute prediction. A second aim (2) was to investigate the performance of DAP and NFI data in a semi-individual tree crown (semi-ITC) approach. Moreover, I aimed to (3) assess how the application on a large area influences the accuracy of forest attribute predictions with DAP, and how environment conditions such as terrain position and geographical location, and the conditions of the image acquisition affect the accuracy. Finally, (4) the development and validation of an operational, large-area forest resource map based on DAP should be described.

The four scientific papers included in this thesis address these four objectives sequentially. The specific objectives of the individual papers are:

Paper I

> *The aim of our study was [. . .] to compare four different 3D remote sensing data sets in the same study area. In particular, we wanted to quantify the accuracy of ALS, AP, InSAR, and radargrammetry for timber volume estimation. Additionally, we analyzed the influence of topography on the accuracy of the four methods.*
> (Rahlf et al. 2014)

Paper II

> *The objective of this study was to apply semi-ITC on a very high resolution (15.6 points m^{-2}) image-based point cloud to predict timber volume, stem density, basal area (G), and quadratic mean diameter (QMD). The performance of the semi-ITC approach will be compared with the ABA.*
> (Rahlf et al. 2015)

Paper III

> *The aim of our paper was to develop and assess an area-based timber volume prediction model for a large study area (24,473 km^2) in Mid-Norway covering heterogeneous terrain and forest conditions using data derived from DAP*

combined with NFI data. DAP was based on imagery from different acquisition dates with changing conditions and was processed separately for the eastern and the western parts of the study area with different image matching settings. An additional aim was to clarify the effects of various factors describing terrain and acquisition conditions on the accuracy.
(Rahlf et al. 2017)

Paper IV

The objective of this paper is threefold; to describe the development of the Norwegian forest resources map (SR16), to evaluate the generated forest information at local scales through comparison of the result to commercial FMIs, and finally to illustrate the gain in precision when using SR16 in addition to NFI sample plots for making estimates at the municipality and regional level.
(Astrup et al. 2017)

3 Usage of 3D remote sensing in forest inventory applications

3.1 3D remote sensing

3.1.1 Measurement of vegetation heights

3D remote sensing provides information about distances of objects from the sensor. To derive 3D information, three general principals are used: measuring the time difference between a transmitted and received energy pulse, interferometry, or triangulation (Beraldin et al. 2010). While the former two are exclusively principals of active sensors, the latter can be applied to data from both active and passive sensors. In earth observation, 3D remote sensing aims to obtain the shape of the earth's surface. In general two different surfaces can be distinguished: the surface with the highest elevation including objects and vegetation, and the terrain surface. The difference between these two surfaces represents the heights of the objects and vegetation.

While not fully consistent in literature, digital representation of these surfaces are commonly referred to as digital elevation models (DEM), with digital surface models (DSM) describing the height of the surface including objects and vegetation, and digital terrain models (DTM) describing the height of the terrain (Li et al. 2004). A canopy height model (CHM) represents the heights of the objects and vegetation above the surface. This terminology is most commonly used for elevation data in raster and triangulated irregular network (TIN) format. Moreover, 3D information can be stored in point clouds, which allow irregular distances between the single height measurements. This format is useful for the storage of 3D data received from sensors with irregular measurement patterns, such as laser scanners (Beraldin et al. 2010).

An important requirement for the extraction of vegetation heights from 3D remote sensing data is the availability of an accurate DTM. A remote sensing system, which can be used to produce highly detailed, accurate DTMs also under vegetation canopies is ALS. Despite its rather high costs, DTMs derived by ALS become increasingly available because of their high value for terrain and land cover analyses.

For forestry applications the heights of the vegetation are the most important product of 3D remote sensing. Remotely sensed canopy heights are determined either by tree height, or by tree height and stand density in combination, which are highly correlated to many important forest parameters such as timber volume and biomass. Using allometric relationships, forest parameters can be derived directly from 3D remote sensing data by using remotely sensed canopy heights (e.g. Straub et al. 2009) or properties of delineated tree crowns (e.g. Villikka et al. 2007). However, standard approaches combine field measurements with 3D remote sensing data, which allows fitting of empirical models to the forest parameters of interest.

3.1.2 Digital aerial photogrammetry

Stereo photogrammetry of aerial images is the oldest method to derive 3D information using airborne sensors. Already in the 19th century, photographs have been used in measuring buildings, terrestrial and balloon surveys. However, it took the development of stereoscopic measurement together with analogue stereo plotters, as well as aviation in the early 20th century to make stereo photogrammetry an effective tool in topographic mapping. Further improvements, which eventually lead to digital photogrammetry, were the introduction of computers into the process in the second half of the century, and the use of digital cameras which allow now complete automation (Kraus 2007, p.3ff).

The principle of stereo photogrammetry is similar to human stereo vision. Instead of eyes, cameras are used to triangulate lines of sight to derive the relative position of an object. Images need to be taken from two or more positions and the interior and exterior orientation of the cameras has to be known or calculated. The object for which coordinates are to be derived must be located on all overlapping images. By constructing lines between the perspective centers of the cameras and the object, the coordinates of the object can be calculated from the images by triangulation (Kraus 2007, p.32ff).

While in the past stereo measurements have been taken manually using analogue or digital stereo plotters, modern methods use automatic methods, i.e. image matching, for finding corresponding points between the images and allow stereo measurements of high density over many overlapping images. Image matching is now implemented in a range of photogrammetric processing software and available algorithms for image matching are plentiful, with each algorithm having specific strengths and weaknesses (Haala 2014). Even though forest canopies can be problematic for image matching algorithms because of occlusions, varying illumination, and shadows with little texture (Gruen 2012), high-quality DSMs of forests can be generated (Baltsavias et al. 2008).

The first use of stereo photogrammetry in forestry was the estimation of parameters of standing trees from terrestrial photographs in the beginning of the 20th century (Müller 1931). The derivation of forest properties from aerial photographs with stereophotogrammetry has been investigated from the 1920s, with e.g. Hugershoff (1933) presenting a method using stand profiles and yield tables to estimate timber volume. Until the end of the century, aerial photographs became increasingly important in forest management inventories. In Norway, by the 1990s, the estimation of volume from aerial images using stereo plotters was a common method in stand-based inventories (Næsset 2014). After the introduction of fully digital aerial photogrammetry, Næsset (2002) presented a new method for forest parameter mapping from aerial images by applying the ABA to point clouds produced by DAP. While ALS has become popular in forestry due to high prediction accuracies of forest parameters and its ability to penetrate vegetation canopy, recent studies have shown that key forest parameters at stand level can be derived from DAP point clouds with comparable accuracy (Bohlin et al. 2012, Nurminen et al. 2013), given the availability of an accurate DTM. The use of DAP in forest inventories and forest monitoring has been investigated especially in the Nordic countries (Järnstedt et al. 2012, Breidenbach & Astrup 2012, Vastaranta et al. 2013, Gobakken et al. 2015), Canada (White et al. 2013, Pitt et al. 2014, White et al. 2015, St-Onge et al. 2015) and central Europe (Straub et al. 2013, Stepper et al. 2014*b*,*a*, Waser et al. 2015).

3.1.3 Airborne laser scanning

Laser scanning (or LiDAR, light detection and ranging) is an active 3D remote sensing technique, which measures the distance between the sensor and the reflections of emitted laser beams. The sensor records the time between emission of a light pulse and reception of its reflection to calculate the distance. Time can be measured either directly (time-of-flight measurement) or indirectly by modulating the phase of the emitted light, with amplitude and frequency modulation as the most common methods. Phase modulation allows the continuous emission of light resulting in higher measurement rate than with time-of-flight measurements. While phase modulation is also more accurate than time-of-flight measurement, it has a much shorter range of usually less than 100 m, which makes it unusable for airborne and spaceborne applications (Beraldin et al. 2010).

Most commercial time-of-flight laser scanners for airborne applications capture discrete returns (or echoes), which represent peaks of the received energy. Such discrete-return ALS data sets are represented as point clouds with each return having a coordinate in 3D space and often additional data such as the intensity of the return and the scanning angle. Todays time-of-flight laser scanners record several returns per emitted pulse (Beraldin et al. 2010), and such multiple returns can occur when the light is reflected from more than one object in its path, which happens especially within vegetation. Full waveform laser scanners, on the other hand, report profiles of all the received energy for each pulse (Mallet & Bretar 2009).

Since ALS is able to penetrate vegetation canopies, it can provide information on terrain below vegetation unlike any other remote sensing technique. ALS is therefore an important tool for topographic mapping, which is one of its primary applications. To obtain terrain heights from ALS data, many algorithms have been developed to identify ground returns (Meng et al. 2010), from which DTMs can be created.

Over the last two decades ALS has become a popular method for forest analyses. While first studies using airborne profiling lasers were already conducted in the 1970s (e.g. Solodukhin et al. 1977), technical obstacles in positioning of the laser measurements had to be overcome. Only with the integration of inertial navigation systems and satellite positioning systems in the early 1990s was it possible to locate ALS returns with accuracies that made the development of operational scanners for topographic measurements possible (Næsset et al. 2004). First studies on the estimation of mean stand height and volume were conducted in Sweden (Nilsson 1996) and in Norway (Næsset 1997*a*,*b*). Building on the results of these initial studies, research on the use of 3D data in forest inventories focused mainly on ALS. Today ALS is used in operational inventories in the Nordic (McRoberts et al. 2010, Næsset 2014, Maltamo & Packalen 2014) and other countries (Næsset 2014).

3.1.4 SAR

Synthetic aperture radar is another remote sensing technique that allows the acquisition of 3D data. Among the processing methods to derive 3D information from satellite SAR are interferometric SAR (InSAR) and radargrammetry, which have been used to model key forest parameters such as height and biomass (Solberg et al. 2013, Solberg, Riegler & Nonin 2015). ith new satellite missions having 3D capabilities for forestry being planned or under consideration, including SAOCOM-CS, Tandem-L and BIOMASS (Le Toan et al. 2011), an increase in the use of space-borne InSAR for forestry applications can be expected. While airborne SAR systems have been used in forestry applications (Neeff et al. 2005, Perko et al. 2011), satellite SAR sensors receive increasingl attention due to their independence of sunlight and insensitivity to most weather conditions (Moreira et al. 2013). Main methods for the extraction of 3D information from satellite SAR are interferometry and radargrammetry, which have been both used in forest parameter estimation (Solberg et al. 2013, Askne & Santoro 2015, Soja et al. 2015*b*,*a*, Solberg, Riegler & Nonin 2015). Especially for forest carbon stock analyses in the tropics satellite SAR is a promising 3D remote sensing technique (Solberg, Gizachew, Næsset, Gobakken, Bollandsås, Mauya, Olsson, Malimbwi & Zahabu 2015, Næsset et al. 2015).

3.2 Merging remote sensing and forest inventory data

The method of merging field and 3D remote sensing is dependent on the spatial resolution of the data. Remote sensing data with spatial resolution similar to the sample plot size can be linked to the field measurements by e.g. assigning the value of the pixel closest to the sample plot center or averaging the values of cells intersecting with the sample plot. For fine resolution 3D data with many observations per sample plot, like

ALS or DAP data, two types of approaches have been used: the area based approach (ABA) and individual tree crown (ITC) approaches.

For the ABA, all remotely sensed heights intersecting with each sample plot are extracted and height distribution metrics are calculated from all heights within each sample plot. Such metrics usually include basic distribution metrics such as minimum, mean, maximum, and variance of the heights, as well as height percentiles. To analyze and describe canopy density the proportion of points above or between certain heights are used. These metrics are then used as independent variables in statistical models fitted to the measured forest parameters. The application of an area-based model requires the gridding of the area into cells, for which all metrics used in the model fitting are computed. Subsequently, the fitted models are used to predict the forest parameters of interest for each grid cell creating a wall-to-wall map. The grid cells should be of similar size as the forest inventory sample plots, because the relationship between the measured properties and certain metrics is dependent on the size of the grid cells unless specific measures are taken (Magnussen et al. 2016). While most studies use rectangular grid cells, which allow an easy handling of the data, areas have also been segmented into hexagons, which resemble the shape of circular sample plots more closely (e.g. Breidenbach, Nothdurft & Kändler 2010, Stepper et al. 2014*b*).

ITC approaches on the other hand aim on estimating properties of individual trees or tree crowns. Such approaches require field data with individually recorded, spatially registered tree measurements and need delineation of tree crowns from the remote sensing data using segmentation algorithms (e.g. Eysn et al. 2015, Vauhkonen et al. 2012, Solberg et al. 2006, Strîmbu & Strîmbu 2015). The methodology is similar to the ABA, but uses the delineated tree crown segments instead of sample plots and grid cells for calculation of metrics for modeling and prediction. Because segmentation errors result in errors of omission and commission of trees, ITC approaches are often biased when aggregated on larger spatial units, such as forest stands. Approaches that have been used to reduce the bias include the semi-individual tree crown approach (semi-ITC) (Breidenbach, Næsset, Lien, Gobakken & Solberg 2010), the combination of the ABA and the ITC approach (Maltamo et al. 2004), and the application of plot level corrections (Yu et al. 2010, Vastaranta et al. 2011). While ITC approaches might be intuitive since trees are a natural unit in forests and feature a higher spatial resolution than ABA, they do not necessarily produce estimates with higher accuracies (Breidenbach & Astrup 2014).

3.3 Forest resource maps and their use in forest inventories

Field surveys give highly accurate information on the measured trees but are expensive and therefore usually only acquired for a sample of the inventory area, from which the properties of interest are estimated for the whole population. Remote sensing on the other hand measures properties of forests which are often less related to the parameters of interest, but is usually less expensive given the large area covered. Statistical models linking remote sensing data with properties measured at the sample plots allow the prediction of the properties of interest also in areas where only remote sensing data are available. The product of such predictions is a map of the forest properties of interest, covering the area wall-to-wall. Forest maps give an overview of the forest resources of an area and can therefore be used to support tactical planning of forest operations. Their main purpose, however, is the support of forest inventories, where forest maps are used as basis for estimates at stand level (McRoberts et al. 2014, Breidenbach et al. 2016, Magnussen & Breidenbach 2017).

In the design phase of an forest inventory, available forest maps can be used to optimize the number and locations of field plots (Næsset 2014, McRoberts et al. 2014). However, remote sensing data covering the inventory area and a model relating the data to the response variable have to be available prior to the field campaign. Maltamo et al. (2011) showed that using a stratified sampling design the number of sample plots can be reduced without decreasing the accuracy of the linking model. Stratification, and the adjustment of sample size and plot size are methods to optimize field sampling according to the remote sensing data.

After the field campaign post-stratification can be used to increase the precision of the estimate (McRoberts et al. 2012). The already measured sample plots are assigned to strata, which should be more homogeneous than the population as a whole. This approach is useful for forest inventories with a fixed design using equal probability sampling, as is often the case for NFIs. The model to create the map which serves as basis for the stratification can be fitted after the field campaign using the sample plot measurements as reference data. By weighting the within-strata measurements according to the strata sizes, estimates for the entire population, the whole area, can be derived, which should ideally be better than the unstratified estimated means and variances.

Forest resource maps from remote sensing can also be used to improve field based estimates or to derive estimates for areas where no or too few sample plots are available. In general, two types of estimators have been used in forest inventories with auxiliary data from remote sensing: design-based and model-based estimators (McRoberts et al. 2014). Design-based estimators rely on probability samples for estimation and inference. Model-assisted estimators (Särndal et al. 1992) use models to improve the precision of estimates. One such design-based model-assisted estimator is the "survey regression" estimator (Rao 2003, p.136). It uses predictions to estimate the mean parameter of interest with a bias correction based on probability sampling, while the variance is estimated from the residuals.

Model-based estimators (e.g. Ståhl et al. 2016) rely more strongly on models than model-assisted estimators and are therefore suitable in areas where design-based estimation is not possible because no or too few sample plots are present. Additionally, because field measurements are only used to fit models using auxiliary data, probability sampling is not necessary. The resulting maps can be used to to estimate forest parameters in small areas, such as municipalities, estates, or even forest stands (Breidenbach et al. 2016, Magnussen & Breidenbach 2017). However, since no bias correction based on field data is included, model-based estimators require more careful modeling than model-assisted estimators (McRoberts et al. 2014).

4 Material and methods

4.1 Study areas

The study areas were located in south and central Norway (Figure 1). The boreal forests were dominated by Norway spruce (*Picea abies* (L.) Karst.) or pine (*Pinus sylvestris* L.). In varying amounts, birch (*Betula spp.*) and other broadleaved species were mixed in.

For Paper I and II two study areas in southern Norway were selected: Lardal in Vestfold County and Odal in Hedmark County, which covered parts of the municipalities Nord-Odal, Sør-Odal, and Kongsvinger. The study areas for Paper III and IV were located in Trøndelag, central Norway. Trøndelag-Vest and Nord-Trøndelag were used in Paper III, Sør-Trøndelag in Paper IV.

The biggest differences can be found between the two southern areas and the northern areas. The two southern areas were smaller than the Trøndelag study areas (Trøndelag-Vest and Nord-Trøndelag 24,473 km^2, total 49,880 km^2) and featured mainly commercially managed forests besides mire and agricultural land. Additionally, though hilly, the southern areas did not show significant differences in terrain and altitude, while the study site in Trøndelag covered various terrain forms and altitudes between 0 and 1400 m above sea level.

4.2 Forest inventory data

An important part of the thesis was the use of NFI data. In Paper II, III, and IV data of the Norwegian NFI were used

The sampling design and the field measurements of the Norwegian NFI are described in detail by Tomter et al. (2010) and in the NFI field manual (Landsskogtakseringen 2008). The sample plots of the Norwegian NFI are located in a 3 km $\times$ 3 km grid, except for mountain forests where the grid is 3 km $\times$ 9 km. The sample plots are remeasured every five years. Accurate positions of the sample plot centers were measured using differential GPS and GLONASS.

In the NFI, a fixed sample plot radius of 8.92 m (250 m^2) is used. On the plot a large range of variables is recorded, including tree, stand, and terrain properties as well as forest health and biodiversity indicators. Position relative to the plot center and diameter at breast height (dbh) are measured for every tree with dbh $\geq$ 5 cm. Using a Vertex hypsometer tree heights of all trees are measured on plots with ten or less trees, while on plots with more trees a sub-sample of approximately ten trees is selected using an adjustable basal area factor. The height of the remaining trees is estimated by

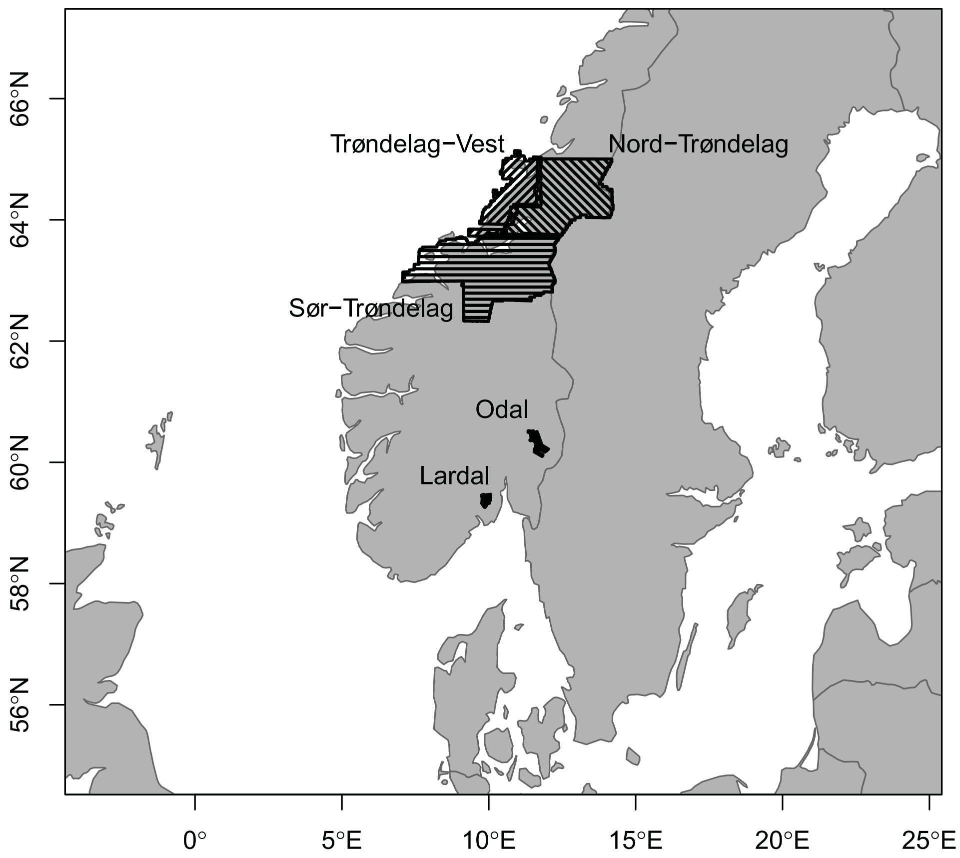

Figure 1: Overview over the study areas used in this thesis.

applying models calibrated with observations from the measured trees. Timber volume is derived using species-specific allometric models for spruce, pine, and birch (Vestjordet 1967, Braastad 1966, Brantseg 1967).

For Paper I a standwise-clustered forest inventory was used, which was originally conducted for an earlier study (Breidenbach et al. 2016). Besides the differences in the sampling grid, the sample plots where measured according to the Norwegian NFI protocol (Tomter et al. 2010). Sample plot centers were selected by stratification. Forest stands were divided into two strata using a stand map of a privious FMI: Stands with an estimated volume > 150 m^3 ha^{-1} and stands with a volume < 150 m^3 ha^{-1}. 20 stands with sizes of 1–3 ha were randomly selected from each stratum. Only stands with a compactness of $\sqrt{A}/P > 0.2$ were selected, with A as the area and P is the perimeter of the stand. The locations of the sample plot centers were set by creating a 20 m $\times$ 20 m grid within each stand and random selection of 7 nodes of the grid.

Table 1: Summary statistics of the ground measured timber volume for Paper I in Lardal (n=170).

	Min	Mean	Max	Std.dev
Spruce	0	153.40	596	129.50
Pine	0	13.37	267	35.80
Deciduous	0	19.68	199	33.93
Total	0	186.45	596	130.70

Table 2: Summary statistics of the ground measured timber volume for Paper II in Nord-Odal (n=40).

	Min	Mean	Max	Std.dev
Spruce	0.00	127.00	454.00	138.30
Pine	0.00	44.35	369.80	78.75
Deciduous	0.00	27.53	195.52	43.18
Total	2.76	198.88	459.16	141.97

Table 3: Summary statistics of the ground measured timber volume for Paper III in Nord-Trøndelag and Trøndelag-Vest (n=483).

	Min	Mean	Max	Std.dev
Spruce	0	49.89	539.24	85.85
Pine	0	9.81	222.04	23.68
Deciduous	0	16.08	290.00	30.06
Total	0	75.78	577.08	92.90

4.3 Remote sensing data

4.3.1 ALS data and DTM generation

ALS data were used for two different purposes in this thesis. In all studies, DTMs were created from ALS ground returns to extract vegetation heights from the 3D data, and, in Paper I, a timber volume model was fitted based on ALS data.

The ALS data in this thesis were collected on behalf of public authorities for various purposes, such as terrain modeling and forest management inventories. For the study sites in Odal and Trøndelag (Paper II–IV) multiple ALS acquisitions from different years were merged. In Lardal (Paper I) a ALS point cloud from a single acquisition covered the whole study area.

DTMs were generated from ALS ground returns, which were classified by the data vendor. DTM raster cell values were populated by averaging the ground returns' heights within each cell. Missing cell values were interpolated from the neighbouring cells. DTM resolution was 1 m × 1 m for Paper I and 0.5 m × 0.5 m for Paper I–IV.

4.3.2 DAP data

The aerial images used in this thesis were acquired with the purpose of orthophoto generation. Acquisitions were part of a national survey program which aims on generating orthophotos at regular time intervals.

Vendors, cameras and aircrafts were varying between the aquisitions. Point clouds from DAP in Paper I, II, and IV were based on a single acquisition. In Paper III–IV DAP data from separate acquisitions were used. Image overlap in Odal, Lardal, Nord-Trøndelag and Trønelag-Vest was 60% along-strip and 20% between-strip, in Sør-Trøndelag 80% and 20%, respectively. Characteristics of the image acquisitions are listed in Table 4.

Image matching for the extraction of 3D information from the aerial images was conducted by external vendors. Point clouds were created using Trible Inpho's Match-T software with the parameter settings "DSM_Mountainious" in Odal, "DSM_Mountainious" in Trøndelag Vest and Sør-Trøndelag and "DSM_Extreme" in Nord-Trøndelag. In Lardal the aerial images were processed to a DSM using BAE Socet Set software.

Table 4: Image acquisition characteristics. Number of images in Lardal was not available (NA). GSD, ground sampling distance.

Site	Camera	GSD	Year	No. of images
Lardal	Vexcel UltraCam X	20	2007	NA
Odal	Vexcel UltraCam Eagle	10	2010	1024
Troøndelag-Vest	Vexcel UltraCam Eagle	25	2013	2402
Nord-Trøndelag (East)	Vexcel UltraCam Xp	35	2010	1548
Sør-Trøndelag	Vexcel UltraCam Xp	25	2014–2015	14057

4.3.3 SAR data

Spaceborne SAR data was used to model timber volume in Paper I. Two sets of 3D data were obtained using different techiques, InSAR and radargrammetry. Three InSAR DSMs were created from three co-registered TanDEM-X StripMap pairs in single look complex format. The DSMs were combined using coherence as weight, since coherence is related to noise and accuracy.

The radargrammetry data were processed using 3 TerraSAR-X StripMap image pairs taken in ascending and descending pass. From each of the image pairs a DSM was created using a SAR stereo-matching algorithm, which was developed by the commercial vendor providing the data. A single DSM was obtained by averaging. Errors and data gaps were removed by automated and manual editing of the DSM. Both DSMs had a grid cell size of 10 m $\times$ 10 m.

4.4 Computations of metrics

In all papers the ABA was applied as it is described in Section 3.2. From the ALS and DAP data following height metrics were derived: minimum, maximum, mean, coefficient of variation (in Paper I), standard deviation of the height (in Paper II and III), and a set of height percentiles. In Paper I and II, canopy density metrics were derived as proportions of points within vertical bins, which were created by dividing the distance between the minimum and maximum point height into ten equal parts (Næsset 2004). In Paper III the percentage of points above the mean height and above 2 m were used as density metrics. In addition to metrics based on point heights following color metrics were computed in Paper II and IV: minimum, maximum, mean, standard deviation and percentiles of each color band values stored in the point cloud, as well as the ratios of the mean band values divided by the sum of all mean band values.

Paper II includes a comparison of ABA with a semi-ITC approach (see Section 3.2). Tree crown objects were segmented using a watershed algorithm on a DAP CHM. For each segment the above described height and color metrics were computed. Geometric properties of the segments were also used as explanatory variables in the modeling.

4.5 Statistical analyses

Various types of statistical models, parametric and non-parametric, were used as linking models. Linear mixed effects models were used in Paper I to account for the hierarchical structure of the field inventory data. In Paper II, kNN models with k = 1 were fitted to multiple response variables (timber volume, basal area, quadratic mean diameter, stem-density) and to a single response variable (timber volume). Additionally, a non-linear logistic regression model (McRoberts et al. 2012) was used. In Paper III simple linear regression models were fitted. Forest parameters were modeled using generalized and simple linear regression models.

Due to the large amount of available variables, explanatory variables were selected using stepwise forward algorithms. In Paper I and III the quadratic terms of the variables were added to the pool of selectable variables to account for exponential trends in the data. The root mean square error (RMSE), relative RMSE and the coefficient of determination (R^2) were used as goodness of fit measures.

4.6 Additional variables

In two papers the influence of additional factors on the forest parameter models was investigated. In Paper I slope and aspect were calculated based on the ALS DTM. To avoid averaging of terrain variables the DTM was resampled in such way, that each forest inventory sample plots was covered by one raster cell.

In Paper III a more comprehensive analysis was conducted using terrain variables, geographic position, camera position of the closest aerial image, and solar position. Terrain variables were altitude, slope, aspect, and topographic position index. Additionally, slope, aspect, and topographic position index were calculated for the surrounding 100 m × 100 m. Geographic position was represented by latitude and longitude. To measure the influence of the camera position we calculated the relative viewing angle onto the plot, considering aspect and slope of the terrain (Figure 2). Solar elevation and azimuth described the sun position at the moment of the image acquisition. The solar incidence angle relative to the terrain incorporated sun position and terrain slope and aspect. The angular difference between the sun light direction and the viewing direction was used to measure the influence of visible shadows in the canopy.

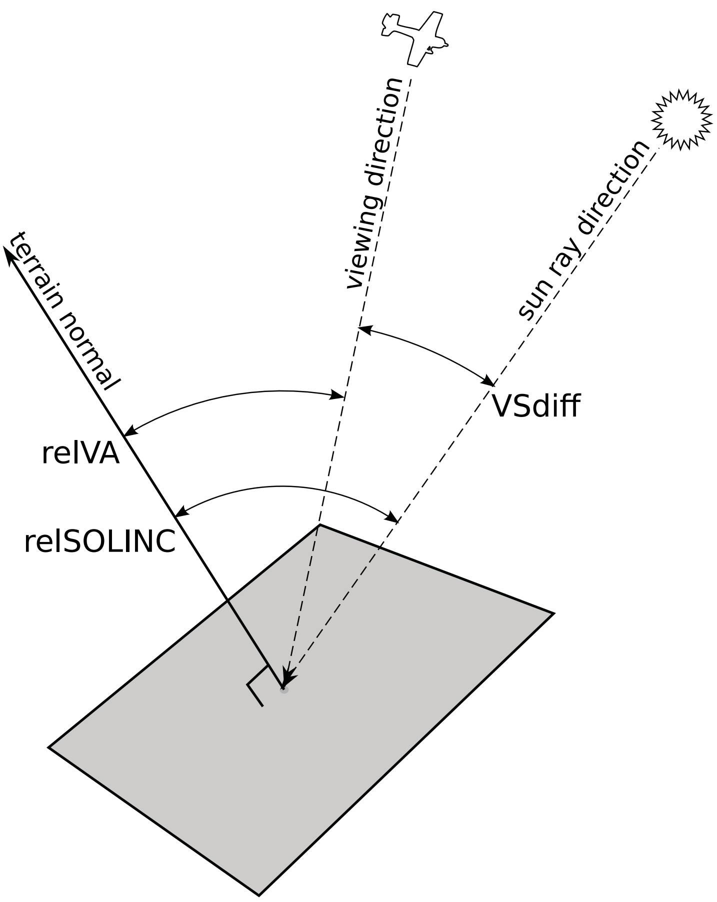

Figure 2: Visualization of the variables relative viewing angle of the camera (relVA), relative sun incidence angle (relSOLINC), and angular difference between the sun light direction and the viewing direction (VSdiff).

4.7 Operationalizing large area forest mapping

The development and and evaluation of an operational, large-area forest resource map were described in Paper IV. For the modeling of forest parameters timber volume, biomass, and Lorey's height some of the methods used in Paper I to III were applied to a large DAP dataset covering Nord-Trøndelag, Trøndelag-Vest and Sør-Trøndelag. Additionally, tree species were modeled using a multinomial logistic model. NFI plots with a dominant species, i.e. where one species group had a proportion of more than 75% of the volume, were used as training data. Beside DAP height metrics also color metrics, elevation and terrain wetness index (TWI), as well as variables from a highly detailed land resource map were used as explanatory variables.

Subsequently, the developed models were used to create a wall-to-wall covering forest map. The application of the models followed the description in Section 3.2. For the validation of the forest map four existing commercial FMI projects from 2015 and 2016 with a total of 27,740 stands were selected. For each stand, timber volume predictions were extracted and totaled, and compared to the the ALS predictions of the FMI.

Furthermore, an existing forest mask was updated using object based image classification on height and color metrics derived from the DAP point clouds. The forest mask could be validated using NFI sample plots, because they were not used in the creation of the mask. The main challenges in creating such a large forest resource map were the handling of large data volumes as well as the combination of the various data sources. However, parallel, tile-wise processing of the point clouds and the use of spatial databases minimized the processing time and difficulties.

5 Results and Discussion

5.1 Comparing DAP and other 3D remote sensing methods (Paper I)

We ranked four 3D remote sensing techniques based on the RMSEs of timber volume linking models. At plot level, the ALS model showed the highest accuracy, followed by DAP, InSAR and Radargrammetry (Table 5). The difference between the data sets is visualized in Figure 3.

The aggregation of the predictions on stand-level reduced the RMSE of all data sets. DAP however was influenced by an outlier, which remained unexplainable. Stand level RMSEs of the models omitting the outlier were 12% for ALS, 13% for DAP, 19% for InSAR, and 25% for radargrammetry, reducing the difference between the ALS and DAP model RMSE to 1% of the mean observed timber volume.

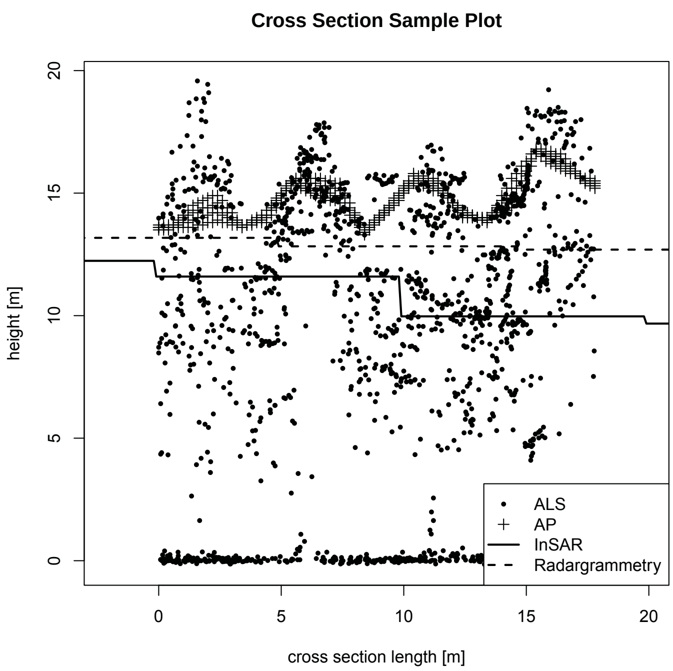

Figure 3: Cross section through a sample plot with vegetation height measurements of the four data sets.

All models at stand level had good model fits, which shows the strong relationship between remotely sensed vegetation heights and forest parameters. The differences between the different remote sensing techniques are not surprising and have been reported earlier, however for the first time these techniques were compared on the same study site, making the differences independent of study design and varying site conditions. A similar study, which was conducted later on a study site in southern Finland, ranked the techniques in the same order (Yu et al. 2015).

Table 5: LOSOCV RMSEs of the timber volume prediction. RMSE (%) is calculated as the percentage of the mean observed timber volume.

Remote sensing data set	Plot-level RMSE (%)	Stand-level RMSE (%)
ALS	19.4	12.4
DAP	31.4	18.1
InSAR	41.0	18.1
Radargrammetry	44.4	23.3

The differences between the DAP and ALS models on stand level is in accordance to the findings by Bohlin et al. (2012) and Nurminen et al. (2013). Timber volume estimates based on DAP have comparable accuracy to estimates based on ALS. Models based on the space-borne SAR data showed lower accuracy, which might mainly be caused by their lower spatial resolution.

5.2 Semi-ITC with DAP (Paper II)

We compared a semi-ITC approach to an area based approach for timber volume mapping. When aggregated on plot level, timber volume predictions using semi-ITC had RMSEs and systematic errors similar to the ABA model. Multivariate kNN models were slightly more accurate with semi-ITC than with ABA, but had larger systematic errors (Table 6).

At segment level the multivariate kNN model of the semi-ITC approach had RMSEs of 175% of the mean observed timber volume, 149% of the mean observed stem density, 160% of the mean observed basal area, and 156% of the mean observed quadratic mean diameter. Despite these rather low accuracies, a comparison to null-models with only the mean observed values as intercept showed that semi-ITC is beneficial for the prediction of certain parameters at segment level.

The segment level results also show that the combination of DAP and NFI data is suitable for tree level analyses. They indicated that both the position of the measured trees is sufficiently accurate in the NFI data, and that the canopy representation from DAP makes segmentation of trees crown possible.

Table 6: RMSEs and systematic errors of the model predictions in percent of the mean observed values. V, timber volume. D, stem-density. G, basal area. QMD, quadratic mean diameter.

Model	Approach	V		D		G		QMD	
		RMSE	sys.err	RMSE	sys.err	RMSE	sys.err	RMSE	sys.err
multivariate kNN	semi-ITC	30	15	46	11	25	12	26	6
multivariate kNN	ABA	30	-3	51	-2	26	-3	35	-1
univariate kNN	semi-ITC	25	5						
univariate kNN	ABA	22	2						
logistic regression	ABA	23	0						

5.3 Large-area application (Paper III)

The application of DAP for large-area forest resource mapping was investigated by modeling timber volume based on reference data from NFI sample plots. The model had a RMSE of 55% of the mean observed timber volume and a R^2 of 0.80. However, the removal of a single outlier would improve the model fit, resulting in a RMSE of 45% and a R^2 of 0.87. The outlier could not be detected by analyzing the explanatory variables, and its removal could therefore not be justified.

The obtained accuracy was lower than reported for earlier studies conducted on smaller study areas (e.g. Rahlf et al. 2014, Puliti et al. 2016). Two factors might be responsible for the lower relative accuracy: The heterogeneity of the study area and the low mean timber volume in the region. Since the relative RMSE is calculated in percent of the mean observed timber volume, a lower mean value causes higher relative RMSEs. The R^2 is similar or better than reported by earlier studies.

We then tested the influence of various terrain and image acquisition variables on the residuals of the timber volume model by including them in the model. The only variable which improved the model accuracy by more than one percentage point was the sun inclination relative to the terrain, which describes terrain normalized illumination at the moment of image acquisition.

5.4 Operationalizing the use of DAP in an NFI context (Paper IV)

The use of DAP data in a large-area operational application mapping forest resources was analyzed. The forest parameters timber volume, biomass were modeled using generalized linear models, Lorey's height using simple linear regression. The biomass and volume models had RMSEs around 50% of the mean observed values and explained about 70% of the variance. The relatively high RMSEs can be explained by low volume and biomass levels, as discussed in Paper III. Models for Lorey's height had RMSEs of around 20% and explained 70% of the variation.

Tree species were classified using multinomial logistic models. For the assessment of the classification accuracy predictions were compared to NFI classifications. Leave-one-out cross validation was applied to all sample plots used in the model fitting. The accuracy was 67% with a kappa of 0.47. This low accuracy shows the challenges of tree species classification using remote sensing data. The values, however, are not much lower than reported by studies dedicated to tree species classification (e.g. Puliti et al. 2016, Korpela et al. 2014).

The updated forest mask was validated using NFI sample plots. The classification showed a high accuracy of 0.89 and a kappa of 0.77 in the confer-dominated, productive lowlands, and an accuracy of 0.95 and a Kappa of 0.63 in the birch-dominated, low-productive mountain areas. Misclassifications were compared with a second land use classification in the NFI data, which showed that the majority of the plots that was misclassified as forest was other wooded land. The remaining misclassified plots where composed of other land use categories with some tree cover such as grasslands.

6 Conclusions and Perspectives

6.1 Conclusions

In this thesis the use of 3D information from DAP in combination with NFI data for forest resource mapping was analyzed. In Paper I–III different aspects of resource mapping based on DAP were investigated: the accuracy of forest parameter models based on DAP compared to other 3D remote sensing techniques, the mapping approach, and the application on a large area. Across the three papers different statistical models for forest parameter prediction were tested, it was analyzed if the use of additional variables describing terrain, image acquisition conditions, and illumination improved model accuracies. Additionally, the suitability of the Norwegian NFI data for forest parameter modeling were investigated. The conclusions which can be drawn from Paper I–III are:

- Forest parameter predictions using DAP data are less accurate than predictions using ALS data, but more accurate than predictions based on satellite SAR data.
- A semi-ITC approach increases resolution and allows prediction at plot level with similar accuracy as with an ABA. However, the complex and time consuming processing makes semi-ITC currently less attractive.
- Forest parameter models based on DAP are stable over varying terrain, illumination, and acquisition conditions, which are properties of large area applications. Model fits could not be substantially improved by introducing additional variables. Only the sun incidence angle relative to the terrain slightly increased the accuracy of a timber volume model.
- The choice of the statistical modeling approach seems not to have a substantial influence on the accuracy when predicting forest parameters using DAP. Good model fits were obtained using both parametric and non-parametric models.
- The Norwegian NFI provides data which is well suited for model calibration. Tree positions are accurate enough to use NFI data in single tree analyses.

In Paper IV these findings were used in the development of an operational forest resource map. The mapped parameters were evaluated using data from commercial FMIs. The final conclusions of this thesis are based to a great extent on the findings of Paper IV.

- While not as accurate as models based on ALS, models based on 3D information from DAP show strong relationships and good predictive ability. It has been shown, that 3D information from DAP can be used to map various forest parameters, as well as forest area itself.

- Combining DAP and NFI data allows the estimation of forest parameters at small scales and improves estimates at larger scales. Stand level estimates of large mapping applications might be sufficiently accurate to be used in forest management planning or in the design of forest management inventories.

6.2 Future perspectives

Forest canopies present difficult surfaces for image matching. Especially solitary trees and open forests show high error rates. Improvement of matching algorithms in these areas might therefore help to decrease errors in forest parameter models. Additionally, the influence of interpolation and smoothing of height measurements, which are inherent to commonly used photogrammetric software packages, has to be analysed.

Both 3D data obtained from aerial images and the spectral information of the images have been used in forest analyses. However, combining these two different data might increase prediction potentials of aerial photogrammetry. The influence of the method of assignment of colors to the point cloud has to be investigated together with the possibility to use colors of two or more aerial images to create multiangle spectral information. Another source of spectral information could be satellite imagery which can provide radiometrically coherent color information over large areas. Fusing satellite imagery with 3D information from DAP might improve model accuracies, especially if the parameter of interest is less related to vegetation height, such as tree species.

Single tree segmentation from DAP data has been investigated by only few studies. While many algorithms used with ALS data can be adopted to delineate trees in DAP data, an algorithm specifically designed for DAP data might be necessary to fully utilize the potential of DAP. Spectral information from the aerial images might again be useful for this application. The variability in airborne spectral data might, however, cause problems for large area applications.

Especially in operational applications, where, beside photogrammetric data, a range of different data sources are available in different spatial extents, data assimilation could be used to combine all data in a consistent way. Data assimilation would also allow the integration of aerial imagery from repeated acquisitions.

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Paper I
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Paper IV
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NIBIO
NORWEGIAN INSTITUTE OF BIOECONOMY RESEARCH

Norwegian Institute of Bioeconomy Research

P.O.Box 115
NO-1431 Ås, Norway
+47 40 60 41 00
www.nibio.no

NMBU

Norwegian University of Life Sciences

Postboks 5003
NO-1432 Ås, Norway
+47 67 23 00 00
www.nmbu.no