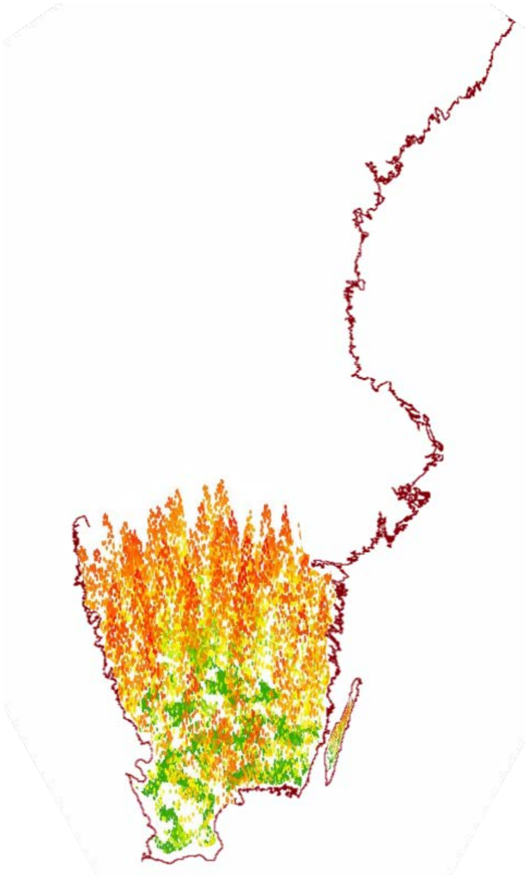
Forest estimates derived from airborne laser scanning data in southern Sweden

A comparison of regional and local model calibration



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Arbetsrapport 446 2015
Master thesis in Forest Management 30hp A2E
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ISSN 1401–1204
ISRN SLU–SRG–AR–446–SE

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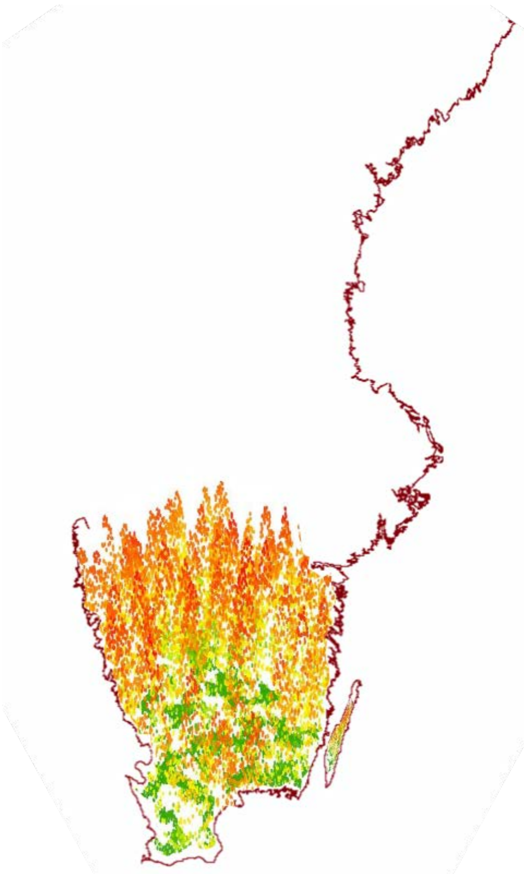

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Keywords: forest inventory, NFI, ALS, regression, calibration

Master thesis in Forest Management at the Dept. of Forest Resource Management
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Sveriges lantbruksuniversitet
Institutionen för skoglig resurshushållning
Utgivningsort: Umeå
Utgivningsår: 2015

ISSN 1401–1204
ISRN SLU–SRG–AR–443–SE 446–SE

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Abstract

Reliable forest estimates are a very important aspect of sustainable forest ecosystems management, but commonly difficult to obtain for large areas. However, with ALS-based forest inventory it is possible to obtain significant estimates. This study tested the application of models currently used to estimate forest variables such as basal area weighted mean height (*H*), basal area weighted mean diameter (*D*), basal area (*BA*) and volume (*V*) at plot level for the whole region of Götaland, a part of Sweden. The models were adjusted by the combination of both laser and NFI field data in order to compare the effect of the use of: 1) two different training datasets (local and regional) and; 2) two types of NFI plots (temporary and permanent). The analyses were done by linear regression. The accuracy evaluation was conducted by means of absolute and relative root mean square errors (RMSE) and bias through cross-validation on plot level and application of the estimations on stand level, which consisted of 65 stands within the study area. Each with an average size of approximately 8 ha. The assessment results on stand level of the two different datasets for all variables validated (*H*, *D*, *BA* and *V*) show RMSE and bias slightly better for the local models (8.8%, 11.8%, 14.0%, and 15.9% respectively), with the highest increase in RMSE for the estimated volume (3%) when applying the regional model (9.7%, 13.8%; 14.7% and 18.8% respectively). Moreover, the models calibrated with only permanent plots performed better than the models calibrated with both permanent and temporary plots. In a second stage of the evaluation, explanatory dummy variables related to geographic position of the forest such as if the forest were located close to the coast, and a variable created by the combination of altitude and latitude were tested. With the dummy variables, NFI plots from the buffer zones of 20 and 50 km around the coast, a slightly lower RMSE for *D* and *BA* were obtained. That indicates that the proximity to the coast has impact on the site characteristics of the stand; therefore, the regression models may operate differently according to the forest type. The analysis implies that the models calibrated with the regional training dataset produced results comparable to the ones produced using models calibrated with local training datasets.

1 Introduction

1.1 Background

Traditional forest inventories have been progressively innovated by the inclusion of remote sensing technologies in their methodologies. Airborne laser scanning (ALS) is one of the latest technologies that has already been implemented at an operational level in the Nordic countries (Naesset et al. 2004; Maltamo et al. 2014). With the rapid development of airborne laser scanning (ALS) systems new perspectives, approaches, and technical opportunities have emerged to obtain large-scale high accuracy 3D data of both ground elevation and vertical features such as the vegetation. In comparison to other previous remote sensing technologies and traditional inventory, ALS-based forest inventory provides accurate and objective forest information in a faster and cheaper manner (Naesset, 2002, Packalén and Maltamo, 2007). That is, currently sustainable forest management requires precise forest inventory information to keep competitiveness, to reduce operational and logistics costs, and to have tools to reconcile and take into account environmental services and other ecological sustainability concerns.

Several countries in Europe have started operations to do countrywide ALS-based surveys. Countries like the Netherlands, Denmark, and Switzerland are already completely surveyed, while others like Poland, Spain and Sweden are still underway (Ahokas et al. 2008; Nord-Larsen and Schumacher 2012; Bolin et al. 2012; Montaghi 2013; Artuso et al. 2003). Likewise, in Sweden, as in most countries, the primary concern for having a countrywide ALS survey was to obtain data to produce a more accurate digital elevation model (DEM) of the entire territory. The updated DEM's purpose is to help in the assessment of the impacts accrued and concerned to global climate changes (e.g. flooding) over the Swedish society. The availability of such data has also boosted and undergirded different interests, since it provides information that can be used for several analyses in different scientific areas (e.g. forestry, hydrology, geography, archaeology etc.).

The new frontier of sensor technology applied to forestry, combined with other technologies, can potentially provide new perspectives, and allow the invention and application of a vast set of tools and techniques to promote better forest management. As well as, innovation of industrial processes and procurement organization, operations, logistics, supply/value chain management of wood and non-wood forest products.

1.1.1 Forest resource assessment and planning

The quantity and quality of forest resources is assessed through forest inventories, which are the main sources of information for forest management and planning (Straub et al. 2010). Today, there is a profuse demand for forest information at a national and global level. One of the main providers of such information is National Forest Inventory (NFI) (Fridman et al. 2014). The first Swedish NFI was conducted in 1923. Since then it has been performed continuously. The primary reason is to provide information to support decision-makers to better endorse forest management planning and environmental regulation at a national and international level (Holmgren 2003).

Forest management is a term used to describe the integration of silvicultural practices and business concepts so that the forest owner's goals would be best met. To have well-managed forests, it is required to have a plan which will provide guidance for (1) implementing activities, (2) predicting future harvest levels, (3) optimizing the use of limited resources, and (4) maintaining or developing habitat areas (Bettinger et al. 2009). Forest management planning usually follows a hierarchy (Figure 1). At the top of the hierarchical level are the strategic plans, which are used to guide the tactical plans, which in turn are used to guide the operational plans. While strategic planning concentrates on long-term management goals (e.g. timber supply for a large area during a long time frame), tactical planning focuses on the allocation of forest operations in terms of time and space, and operational plans concern treatments that should be done at short intervals such as thinning (Bettinger et al. 2009).

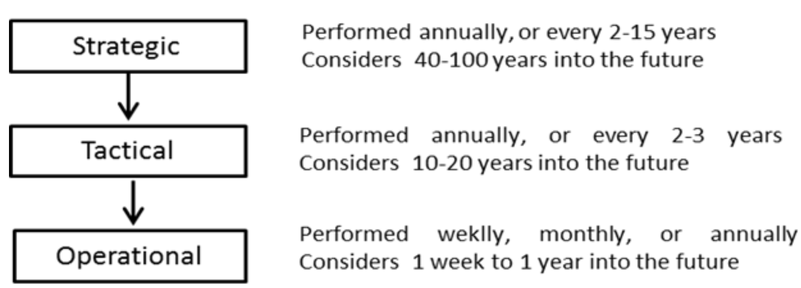

Figure 1. A hierarchy of natural planning processes (adapted from Bergseng et al. 2015, p.8)

Forest inventory is "*an accounting of trees and their related characteristics of interest over a well-defined land area*" (Scott and Gove 2002, p.1). Inventories are planned and conducted at different levels (national, regional, stand and tree level) according to their purpose and the area size. The primary purpose is to support decision-makers in forest management by the quantification of the growing stock, which measures the volume of all living trees in a given forest area. Today, other aspects of the ecosystem have also been quantified; however, due to its economic value, wood remains the main focus for forest inventories (Scott and Gove 2002). The ideal forest inventory design would be the one which does a complete enumeration of all trees within an area of interest. However, this design is not feasible since it is costly and time consuming. Thus, most forest inventories are based on field sampling, which is strategically designed depending on the forest type, site topography, area size and available budget (Scott and Gove 2002). Sample plots are mainly circular, but can also be rectangular or angular count sampling plots, in which trees are selected and measured using a relascope.

For strategic inventories different probability sampling techniques such as simple random, systematic, and stratified sampling are usually applied. The choice of the sampling method will depend on the required accuracy and budget available. Usually, large-area sampling is based on clustering the plots in order to reduce costs. Like many of the inventories conducted worldwide, Swedish NFIs are also based on objectively selected field samples (Tomppo et al. 2010). Its methodologies have gone through many changes over the years for better performance, as well as to attend to the exigencies demanded by society. For instance, Sweden was one of the first countries to adopt an inventory design that assesses the entire forest resource of the country every year (Fridman et al. 2014). This new approach has contributed to reporting up-to-date information countrywide every year, as well as for international conventions such as the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol. One of the main challenges that the Swedish NFIs crew has been facing is keeping and expanding the long time series of traditional data while at the same time including new kinds of information that have been newly required (Fridman et al. 2014). However, the authors believe that basic measurements that have been already performed by the NFIs such as land use, trees, other vegetation, and site conditions have potential for answering a wide range of new questions such as biodiversity conditions and greenhouse gas emissions.

The assessment of forest inventories usually ends when reliable information in terms of mean values or totals, and the corresponding accuracy and precision have been computed (Bergseng et al. 2015). Reliable forest information forms the basis for key management decisions.

On the other hand, inaccurate forest information leads to undervaluation or overvaluation of forest resources, which in turn results in poor forest policies, planning, and management that could consequently could contribute to a decline in area, health, stock, and flows of forest resources (World Bank 2008).

Strategic level inventories are traditionally conducted by ground measurements, and they can provide more detailed forest information. However, this method has shortcomings when covering large areas since it is time consuming and expensive (Vauhkonen 2014). Moreover, it will not provide any map if not combined with remote sensing data. Therefore, inventory methods that can provide broader information framework in a shorter time and for a lower cost would be the ideal. For a long period, remote sensing technologies have been used as auxiliary information for planning the forest inventories. For example, by using aerial photography for stand delineation. Nevertheless, due to technical innovation, the information content of remotely sensed data used in forestry has been enhanced, especially with the introduction of forest inventory approaches based on ALS. Although ALS systems do not accurately measure the understory vegetation, it has been seen by Nilsson (1996), Hyyppä and Hyyppä (1999), Lefsky et al. (2002), Naesset (2002) as a potential tool to be used in forest inventories. Today, ALS-based forest inventories have been used in an operational way for large areas using a standwise approach in Norway, Sweden and Finland (Naesset et al. 2004).

1.1.2 Swedish forestry outlook

Sweden has large areas dominated by productive forests, covering 23.3 million ha of the country's land. Forestry forms a crucial share in the national economy. Although Sweden holds only 1% of the world's commercial forest area, it provides 10% of the world's sawn timber, pulp and paper (Barklund 2009). The total growing stock is composed of 45.2% of Norway spruce *(Picea abies)*, 30.5% of Scots Pine *(Pinus sylvestris)* and the remaining 24.3% is mostly broad-leaved species, in particular, Birch (*Betula* spp.) (Swedish NFI 2014). Forests are mainly managed with clear-felling practice and a rotation period of approximately 100 years. About half of the forest land is owned and managed by a few large forest companies or other large organizations. The other half of the forest land is owned by about 227,000 family enterprises. The average family enterprise holding is 50 ha; and the size typically varies from 2 to 200 ha (Barklund 2009).

The Swedish NFI is a strategic inventory on national level conducted on a regular basis by the Swedish University of Agricultural Science (SLU). For instance, every year about 11,000 field plots are sampled all over the country (Swedish NFI 2014). Limited sample size is one of the main factors that can prevent estimators from providing reliable estimates (McRoberts et al. 2014).The Swedish NFI produces statistics and data for forecasts, rather than maps. Large companies also make strategic plans with objective sampling methods which are primarily used for statistics and forecasts, but not maps. Both companies and family enterprises use forest standwise tactical management plans that consist of a stand map based on forest variables and treatment recommendations, which traditionally has been based on wall-to-wall maps made from airphoto interpretation and subjective field inventories. These plans are normally renewed every 10-15 years. Operational plans, in turn, are conducted on stand level and are done before the application of any treatment. In the case of the family enterprises, the plans are a requirement for a voluntary environmental certification of their forest properties. With remote sensing, in particular laser scanning, one can use the field plots from the strategic level, or collect new field plots if needed, and automatically create detailed wall-to-wall maps that will support the tactical plans. In addition, there are possibilities to improve the statistics computed for the strategical plans by combining the field plot data with the remote sensing data. Unlike in Norway and Finland, the Swedish state does not subsidize inventory plans; consequently, the development of plans is not coordinated among the neighbouring properties, which makes it difficult for the consultants to make plans for private family-owned forests with small land holdings through the use of remote sensing data trained with field surveyed sample plots, since the cost for collecting the sample plot data needed would be too high (Olsson et al. 2013).

Forest variable estimates produced using "kNN" or "k-Nearest Neighbour" method, a method developed in Finland in 1990s (Tomppo 1993) has been used in Sweden to do countrywide raster databases of forest resources based on satellite data (Landsat or SPOT) calibrated with the NFI sample plots (Reese et al. 2003). Such forest estimations have been produced every 5 years since 2000 and mostly used by various government agencies at national and regional levels in making policy decisions regarding forestry, energy and environmental quality management, as well as forest companies for evaluating the consequences of these policies on their practices (Tomppo et al. 2010). Nevertheless, these maps are considered too coarse for operational use in the forestry sector. The combination of satellite data and NFI plots usually presents low accuracy when assessed on a pixel level. There are many reasons for the low accuracy, but one of the most common is the inclusion of outliers due to the spatial mismatch between the satellite image pixels and the field plots (Tomppo 1993).

1.1.3 LiDAR

LiDAR stands for light detection and ranging. It is a technology that produces distance measurements based on the return time of emitted light. LiDAR data can be collected from different platforms such as a tripod (terrestrial laser scanning), an airplane (airborne laser scanning) and from a satellite (spaceborne laser scanning). In the Nordic countries, terrestrial and airborne are the two most commonly used platforms for collecting LiDAR data for forestry. However, terrestrial systems are used for fine scale data collections and still mainly applied on a research level, whereas Airborne Laser Systems (ALS) are used to collect datasets at local, regional and national scale and has already shifted from research to operation level. The ALS system is broadly composed of four parts: i) laser ranging system, which emits laser pulses normally in near infrared or green wavelengths and records the ranges; ii) scanning system, like an oscillating mirror or a rotating prism, to scan the area of interest in a particular pattern; iii) GPS receiver which gives the altitude and location of the platform; iv) IMU (inertial measurement unit) which tracks the orientation (yaw, pitch, and roll) of the platform as well as its acceleration in 3 dimensions (3D). For more detailed information about ALS systems see Wehr and Lohr (1999). Studies have already established that ALS data can provide very accurate elevation models (Reutebuch et al. 2003). From the geo-referenced point cloud it is possible to obtain digital surface models (DSM) – which are the first visible surfaces one can see from the top (e.g. airplane) including all the objects on the earth's surface (e.g. tree canopies, roofs, etc.) and digital elevation model (DEM) – which is the ground surface obtained by filtering the ALS returns from only the earth surfaces. These two can then be used to calculate the canopy height model (CHM), which is the difference between the DSM and DEM. The CHM comprises information related to forests.

ALS systems provide an opportunity to capture dense point data defining not only the canopies but also the ground surface through the point measurements that penetrated the canopy. Multi-return LiDAR systems that can register more than one return from the same laser pulse have enhanced these capabilities. Thus making it possible to “map” the canopy, the bare earth, and many of the vertical and horizontal structural characteristics such as canopy height, volume, and basal diameter.

Forest inventory techniques using ALS data mainly consist of two methods: single tree method, which is not used commercially yet, and area based method, which is used operationally. Single tree methods rely on high density data to delineate individual tree crowns and use tree crown characteristics and dimensions to obtain forest estimates. Area based methods, on the other hand, use a 3D point cloud for a sample plot to characterize its ground surface and the vertical distribution of the biological material in the vegetation layers above the ground surface. Various parameters that characterize vertical distribution of the point clouds are also related to inventory metrics such as point cloud height percentiles being related to canopy density, penetration rates being related to leaf area, etc. (Hollaus et al. 2014).

Researchers in Sweden have been widely studying different remote sensing techniques to improve forest inventory (e.g. Nilsson 1996, Reese et al. 2003, Olofsson et al. 2014, Granholm et al. 2015). ALS was first used in Sweden in 1991 with the use of the full waveform FLASH system (Nilsson 1996). The early studies in Sweden were not very encouraging due to low accuracy data caused by the unavailability of accurate GPS positioning. The technological improvements (laser electronics and IMU systems), as well as availability of precise GPS in ALS, the data quality and the data collection efficiency, improved drastically over the last decade. For instance, the FLASH system used had a pulse repetition frequency (PRF) of 160 Hz and point measurement accuracy of about 2.5 m (Nilsson, 1996; Naesset et al, 2004), whereas systems used for the study, like Leica ALS60, have a PRF of up to 200,000 Hz and point measurement accuracy of 0.2 m. The improvements have been occurring continuously, e.g. ALS systems like Titan Optech operate with a maximum PRF of 900,000 Hz, which is the combination of three active beams of 300,000 Hz each.

A number of studies around the world have been conducted to investigate the effects of various aspects associated with collection and use of ALS data in forestry such as different laser systems, different point cloud density, and forest area/type, as well as explore different approaches to extract forest information relevant to forestry, like forest metrics. For instance, one of the pioneer studies using profiling LiDAR done by Nelson et al. (1984) states that the stand profile component presented a linear relationship to crown closure, thus could potentially be used to obtain tree height. Holmgren (2004) reports that the estimation error of forest variables (e.g. mean tree height, basal area and stem volume) does not change much when using point cloud densities between 0.1 and 4.3/m² in the area based method. Later, a similar study (e.g. Maltamo et al. 2006) found comparable results. Simulations performed by Holmgren et al. (2003) to evaluate the effect of scanning angle on ALS measurements of forest attributes shows that height measurement is not significantly affected. However, in forests with long tree crowns and with few stems per hectare, effects are more apparent. Vegetation ratio is more affected by scanning angles, especially if the angle is greater than 10º. Naesset (2009) found that the use of different sensors, change of the pulse emission frequency and flight altitude influenced estimation of vertical height profile and also affected the penetration level.

1.1.4 Nationwide Airborne laser scanning

In 2009, the Swedish National Land Survey (Lantmäteriet) started a countrywide ALS data survey with the purpose of constructing a new DEM (2m x 2m grid) to upgrade the elevation maps of the entire country. The survey is funded by the government and encouraged by the increased need for flood risk mapping under climate change scenarios. The scanning project period is from 2009 to 2015. Southern Sweden, which has more broadleaved forest, was mainly scanned during the spring and autumn during leaf-off periods, whereas northern Sweden has been mostly scanned during the summer period. The survey was planned such that each block was scanned within a minimal time period and with the same system. The laser data is available for several government institutions for free; and private companies at low cost.

A number of studies from Scandinavian countries and North American countries show ALS data successfully providing good results for forestry (Naesset 1997a, Maltamo et al. 2006, Thomas et al. 2006). However, the national laser scanning dataset is likely not ideal for area-based estimates, since the maximum scanning angle is 20º (Holmgren et al. 2003). Moreover, the data are collected with different sensors and at different dates. On the other hand, earlier studies have shown that it is possible to produce sufficiently good large area forest products from this type of data and that the ALS estimates could be trained with NFI field plots (Hollaus et al, 2009; Maltamo et al. 2009; Nord-Larsen et al. 2012).

One of the most important products from the national ALS campaign is the DEM, since it provides a ground reference for various types of 3D remote sensing products that can be used for forest estimates (Olsson et al. 2013). For example, the new national DEM can be used as ground reference to generate vegetation heights from 3D point clouds by automatic stereo matching of aerial images (Bohlin et al. 2012), which in turn can potentially be a source of data for updating a national forest database.

An increased availability of high quality and up-to-date spatial information about the forest resources is beneficial. Hence, through the government initiative there is an ongoing project, "*Prediction of forest parameters using airborne laser scanning data,*" which is run by the Swedish Forest Agency (Skogsstyrelsen) in co-operation with Swedish University of Agricultural Science (SLU) to produce countrywide estimates of different forest variables through the combination of ALS and NFI data. The Swedish NFI provides geographically-located forest data from relatively small circular plots (7 or 10 meters radius), which in combination with ALS data can be used to estimate forest variables such as tree height, stem volume, basal area, and diameter. In the project, wall-to-wall raster maps with predicted forest variables such as mean volume, basal area, height and biomass are derived for the whole Swedish landscape by combining both NFI and ALS data. The predictions are calculated per block (size 25 x 50 km^2), which is the scanning area. These predictions made per "block" will be referred to as "local" predictions. In order to obtain enough NFI plots (approximately 300 plots) to calibrate the local regression models, plots measured within an age gap maximum of 5 years from when they were laser scanned are chosen; however, tree growth is forecasted or back-casted to the same year it was laser surveyed. Although the estimates are calculated per block, the training data in the current "local" strategy may also be collected from nearby blocks, as sometimes a block may not have enough plots that meet all the criteria established.

According to Görgens (2014), there are two important requirements to use field data to calibrate ALS data: 1) field plots need to be precisely geo-referenced so that correct geo-location in the 3D laser point cloud is possible; 2) field measurements should be collected at the same time as the ALS survey. The latter requirement has been solved in the Swedish national project for forest estimation using the "local" strategy by forecasting or back-casting the field data with growth functions, after removing outliers due to for example cuttings or bad geometrical fit.

In this study, we are interested in answering the following question: How would the use of regional regression models calibrated using NFI and ALS data from a whole region affect the quality of the predictions compared to local regression models that are currently used? Using NFI data from a larger area means that plots from a shorter time period can be used to derive the regression models needed; that is, if one takes a larger area, then more NFI plots will be available. Therefore one can select plots that were measured, as well as laser surveyed in the same year, avoiding the errors that might happen in the forecasting/back-casting process. The use of field data from a short time period should have a positive effect on the estimation quality since the risk of including field plots that have been subject to changes e.g. cuttings, will be minimized. Even though ALS-based forest estimates have been already providing higher reliability compared to current forest inventory methodologies there is still scientific quest for better applicability of ALS data.

This thesis is built on the project run by SLU and Swedish Forest Agency for production of countrywide forest estimates. Within the project's objective, this study aims at contributing with some results and insights on the use of ALS-based techniques for mapping forest estimates at a regional level through the comparison between the use of two different training datasets (local and regional) and two types of NFI plots (temporary and permanent) to estimate forest variables for a whole region of Sweden (Götaland).

More precisely, the following hypotheses were addressed:

(i) Laser data in combination with NFI plots from a large area can be used to estimate regional forest parameters with similar or better accuracy than estimates based on more local NFI plots collected during a longer time period.

(ii) In the case of using only permanent NFI plots from a large area for a regional model calibration, the models performance is equal or better than by including temporary NFI plots.

(iii) The inclusion of information related to geographic position of the forest such as coastal vegetation (altitude 20 or 50 km buffer zones along the coast), latitude and altitude can improve the models performance for the estimation of forest variables at a regional level.

2 Materials and methods

2.1 Study Area

The study was conducted using data from the whole Götaland region in southern Sweden (Figure 2). Gotland, which is an island located in the east side of the region was; however, not included in the study because its landscape varied highly from the others.

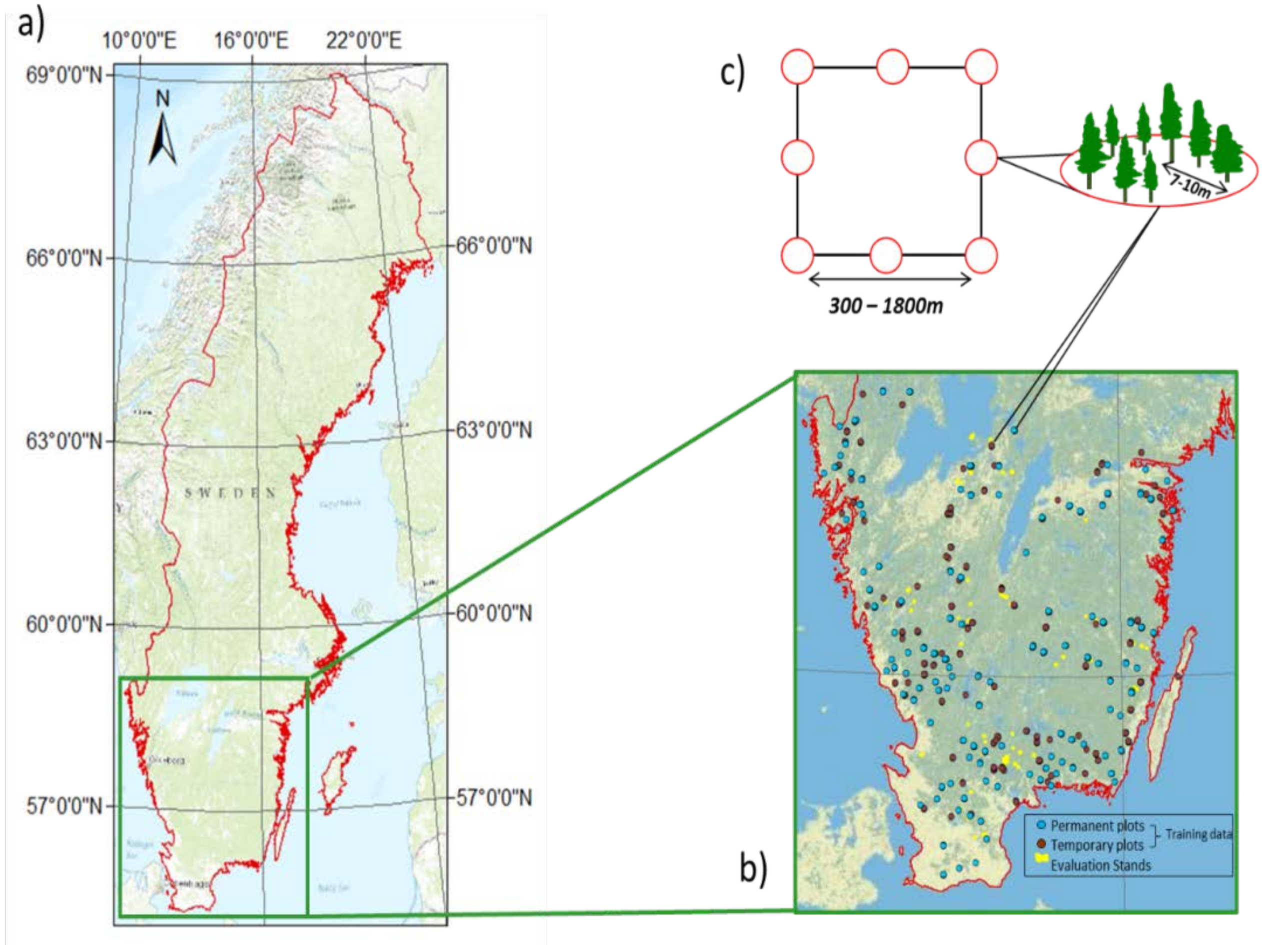

Figure 2. a) The area of interest is shown in green: Götaland region, south Sweden; b) it shows the distribution and location of the clusters with training data and validation stands; c) it shows the NFI plots tract shape and plot sizes. Source: ©OpenStreetMap contributors, and the GIS user community.

The total region's land area is about 8.7 million ha of which 5.5 million ha is defined by the Swedish NFI (2014) as forest lands. In order to facilitate international collaboration, in 2009

Sweden adopted the definition of forest used by the Food and Agriculture Organization (FAO)[1] (Tomppo et al, 2010). The region is the most populated area in Sweden. In 2012, it had approximately 50% (4.6 million) of the total Swedish population (Högman, 2014). Götaland's climate has a winter that is shorter and milder compared to the rest of the country. Temperatures during the summer vary from 15 to 25 °C (Swedish Institute, 2015). The area is part of the boreal biome, and its landscape is composed by a mosaic composed of lakes, wetlands, and extensive stands of forest dominated primarily by Scots pine (*Pinus sylvestris*) and Norway spruce (*Picea abies*). Only a small zone in the southern tip of Sweden is mainly covered by deciduous forests (Barklund 2009). Common deciduous tree species include birch (*Betula spp*), European aspen (*Populus tremula*) and alders (*Alnus spp*). Forestry operations are common all over the region.

2.2 Materials

The materials used to produce the forest variables are a combination of forest metrics derived from ALS data and NFI plots. Each of these materials is described below.

2.2.1 NFI plots

The reference data is taken from the Swedish NFI which is based on field samples collected annually by systematic ground measurements. The measurements are implemented within defined circular plots, which are clustered into tracts and distributed all over the country. Each tract consists of 8 to 12 sample plots and can be quadratic or rectangular. The country is divided into five regions with decreasing sampling intensity towards the north. The tracts vary in size between different parts of the country (Tomppo et al. 2010). For instance, in the southern tip of Sweden, the distance between the plots in a tract is 300 m. Additionally, there are two kinds of tracts: temporary and permanent. In the temporary tract, plots are only surveyed once and have a radius of 7m, whereas in the permanent tract, plots are resurveyed every 5 years and have a radius of 10m. Proportionally, only one third of the tracts are temporary all over the country. The distance between tracts also varies. While in the south it is 3 km, in the north it is 10 km.

[1] In Sweden the term forest land is defined using the same definition proposed by the UN's Food and Agriculture Organization (FAO) which defines forest as "*Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use* (FAO 2004, p.16)."

All plots have been positioned in field using Global Positioning System (GPS) receivers sharing about 5m accuracy. During 2013, new and better GPS positions were collected for 3083 permanent plots across the entire region of which 94 were located in Gotland. Therefore, there was a total of 2989 permanents newly surveyed in the study area. For the tested regional training dataset, a total of 649 forested plots (including temporary and permanent) were in accordance to the plots selection criteria defined (described in chapter 2.3.1). Of the 649 plots, only 493 remained after removing outliers, of which 267 were permanent plots. Outlier's removal occurred in order to eliminate field plots that were deemed to introduce bias in regression modelling. For example, plots located in areas where practices like cutting occurred after the field inventory and before the laser scanning and plots with low positional accuracy. The correlation coefficients can be substantially influenced by outliers (Chatterjee and Hadi, 2006). The outliers were removed using robust regression, where 15% of the plots having the largest deviation between field-observed and estimated values for tree height and stem volume were eliminated. The training data were used to calibrate the regional regression models used to estimate forest variables at a plot level. In this study, the estimates used from NFI sample plots were as follows: basal area weighted mean height, basal area weighted mean diameter, basal area and volume. A summary of the statistics of the field plots is given in Table 1.

Table 1.Statistics of used regional NFI plots inventoried in 2010-2012 after the exclusion of 15% of outliers

	Permanent and Temporary			Only Permanent plots		
Variables	Mean	Std. dev.	Range	Mean	Std. dev	Range
Height (m ha^{-1})	14.9	5.2	3.0 - 27.0	14.9	5.2	3.0 - 28.6
Basal area (m^2 ha^{-1})	22.5	10.1	0.9 - 57.9	22.5	9.6	2.7 - 53.2
Volume (m^3 ha^{-1})	170.7	107.9	3.4 - 582.7	170.1	106.7	7.5 - 660.4
Diameter (cm ha^{-1})	21.0	9.1	3.0 - 56.6	21.1	9.0	3.4 - 52.1

2.2.2 ALS data

The nationwide ALS survey has operationally started in 2010 and is predicted to be finished by the end of 2015. The area of interest was laser scanned in 2010, 2011, and 2012. For this study, we are using only data collected during leaf off conditions in spring and fall (e.g. April, May and October). The country was divided into 11 scanning production areas, having a total of 387 blocks of 25 x 50 km each (Figure 3). However, we are using data from scan areas A, B and C. A total of 50 blocks (58,750 km^2) were used, such that all of them were scanned using either

Leica ALS50 or Leica ALS60. The laser pulses ranged from 0.5 to 1.4 returns/m²; and maximum scanning angle used was 20º. A summary of the laser scanner and flight data is provided in Table 2.

Table 2.Summary of the laser scanning operation and flight used for regional calibration

System	Leica ALS50, Leica ALS60
Flying altitude	1,740 to 2,300 m
Pulse repetition frequency	70 to 104 kHz
Scanning angle	up to 20°
Average point density	0.5 to 1.4 returns/m²
Footprint size	0.4 to 0.8m
Horizontal accuracy	0.6m
Vertical accuracy	0.2m
Season	leaves off (fall and spring)
Scanning years	2010, 2011, 2012
Flight line overlap	20%
Flight speed	145 to 155 knots
Scan area overlap	200m

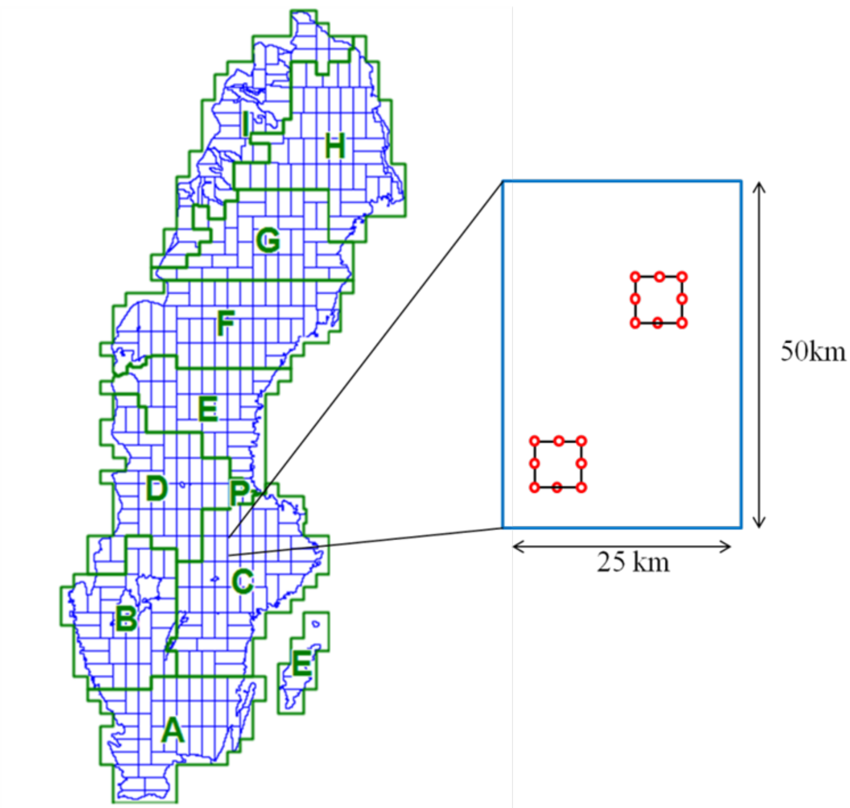

Figure 3. The demarcation in green shows the scanning production areas. The blue rectangles represent the scanning blocks. The red circles represent the NFI reference plots.

2.2.3 Validation dataset

Validation dataset consisted of 65 forest stands that have been managed by the Swedish state forest (Sveaskog) and is located within the study area. The stand selection followed two requirements regarding its location:(1) they should be within areas that have been laser scanned during the leaf off season, and (2) they should be within areas laser scanned with the same scanner system. The size average of the stands is approximately 8 ha with an average of 8.5 plots per stand measuring 10 m radius each, where 8 plots were located entirely within the stand and only 50% of the 9th plot was located within the stand. The inventory of the field plots were performed in 2010.

2.3 Methods

A general view of all the steps taken to derive forest estimates from ALS is shown in Figure 4.

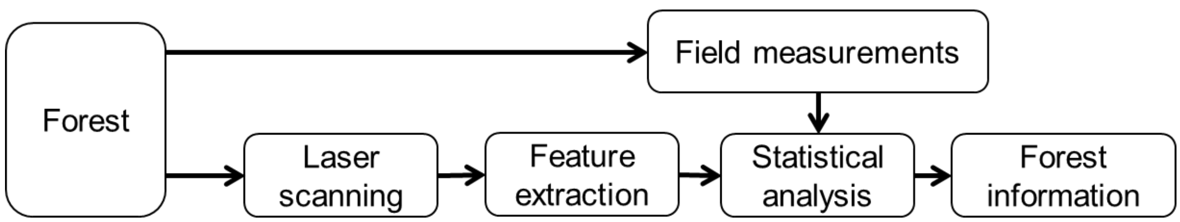

Figure 4. Retrieval of forest information, using an airborne laser scanner system (Holmgren 2003).

Normalized 3D point clouds were used. It is obtained by subtracting the elevation values of the DSM from the DEM in order to get height above ground instead of altitude. Point clouds of NFI plots were extracted using coordinates of the samples surfaces and their respective radius. Next, a variety of statistical laser metrics corresponding to the NFI plots were computed using both the Clipdata and CloudMetrics functions in FUSION, an open source software (McGaughey, 2012). To evaluate regional calibration the same metrics presently used in local modelling calibration were selected, which are: height percentiles (*P95*, *P90* and *P80*) and ratios of returns from vegetation above a specified threshold of 1.5m (more details later). The use of a threshold was introduced by Nilsson (1996) and is often used to calculate the height measurements to avoid ground and undergrowth vegetation points.

The area-based forest estimation approach introduced by Naesset (1997a and 1997b) was used to estimate the forest variables. This approach essentially consists of two steps:

a) First, a regression model is built by using a sample of objectively measured field training plots for the prediction of forest variables based on laser-derived variables.
b) Secondly, the forest variables are predicted using the above models within the raster cells of similar size as that of the field plots.

The raster cell estimates can be aggregated within predefined forest stands and used to support forest planning. However, validation at forest stand level should be performed before forest management planning is done using forest stands as decision units (Holmgren, 2004).

2.3.1 Selections of the field data to calibrate laser data

For the regional model calibration, the criteria used for selecting field plots for calibration of the laser data are: (1) all plots have been field surveyed the same year as they were laser scanned; (2) areas must have been scanned by the same scanner system; (3) areas must have been scanned during the same season. For the local models, the criteria were similar to the one mentioned above, changing only criterion (1), all plots must have been field surveyed within 5 years of being laser scanned. About15% of the plots were identified as outliers and removed from the datasets used for both local and regional calibration. Thereby, there were 267 permanent field plots used for the regional calibration model. Local model calibration is commonly done with about 300 permanent field plots fulfilling their respective criteria. The plots for regional model calibration were chosen within the scanning areas (A, B and C shown previously).

2.3.2 Modelling and accuracy assessment

Modelling was done using linear regression analyses (Equation 1). Linear regression analysis comprises statistical analysis in order to verify the existence of a functional linear relationship between the response variable *(Y)* and one or more of the explanatory variables *($X_1, X_2, \dots, X_n$)* (Chatterjee and Hadi 2006).

$$Y_i = \beta_0 + \beta_1 X_1 + \dots + \beta_n X_n + \varepsilon_i \quad (1)$$

Where, $\beta_0, \beta_1, \dots, \beta_n$ are the regression coefficients, which are the unknown constant values that will be predicted from the combination of laser data and training data from the Swedish NFI. $X_1, X_2, \dots, X_n$ are explanatory variables, and $\varepsilon_i$is the residual or error term.

For forest estimation at a regional level, modelling was carried out for two training datasets, one containing only permanent NFI plots and the other containing permanent plus temporary NFI plots. At a local level, modelling was conducted with different training datasets (a total of 50). That is, there are 50 scanning blocks in the whole region and the models for each block were derived using the 300 geographically closest NFI plots field measured during the period of 2009 to 2013. For the comparison, the arithmetic mean of all the estimates per block were evaluated against the estimates obtained from the regional models.

The regression models used have no more than two explanatory variables, in order to avoid complexity and keep the models as simple as possible. According to Chatterjee and Hadi (2006), the inclusion of many variables can lead to adaptation of the models, where there are problems with the explanatory variables being correlated to each other.

Regression functions were derived for each forest variable (response variable) that was of interest to estimate and the different metrics calculated from 3D point clouds were used as explanatory variables. Four response variables were estimated: mean tree height, mean tree diameter, mean basal area and mean volume.

The response variable volume was not suitable for analysis. It had an exponential relationship with the explanatory variables, which goes against the assumption that the regression model should be linear. Therefore, to ensure linearity the variable was transformed to square root volume. All predicted mean tree heights and tree diameters in this study were basal area weighted, described in equations 2 and 3:

$$h_{gv} = \frac{\sum_{i=1}^{n} g_i \, h_i}{\sum_{i=1}^{n} g_i} \tag{2}$$

$$d_{gv} = \frac{\sum_{i=1}^{n} g_i \, d_i}{\sum_{i=1}^{n} g_i} \tag{3}$$

where g_i is the *i*th tree's basal area (cross-sectional area at breast height), h_i and d_i are the height and diameter of the tree, respectively. In the manual for photo interpretation, Allard et al. (2003) says that basal area weighted height is preferred as a measure for the estimation of stand's tree height. According to the authors the main reason to use this approach is that it is inclined to represent values of bigger trees more than the undergrowth.

In order to compare the effect of the use of different training datasets, each forest variable was fitted using the regression models defined by SLU for performing forest estimation at the local level (scan block of size 25km x 50km). SLU has been using one model for mean tree height (*H*) estimation, two models for basal area (*BA*), and four models each for diameter (*D*) and volume (*V*) estimation, see Table 3. For the forest variables which have more than one model defined (e.g. basal area, tree diameter and volume) the analyses and selection criteria for the best model were based on the highest adjusted coefficient of determination (R^2). In addition the significance (p> 0.05) of the models coefficients (β_i) and the scatter plot of their residuals were analyzed. The use of scatter plot graphics analysis Chatterjee and Hadi, (2006) can help to identify systematic errors. The response variable *V* was then transformed to the original scale.

Laser metrics were derived from the 3D ALS point cloud for each grid cell (12.5 x 12.5 m), which corresponds to the size of the temporary NFI plots. The sizes of the grid cells were defined based on the size of the NFI plots, which have areas of 154 m^2 and 314 m^2 for temporary and permanent plots respectively. Regression models were eventually used to estimate the forest variables (*H, D, BA, V)* for each grid cell, and calculating the mean over grid cells as an estimate for the whole study area (regional and local areas).

The validation of the models was conducted using two methods. First, the leave-one-out cross-validation technique (Weisberg,1985) was used. Leave-one-out cross-validation is done by using a single observation as validation data and the remaining observations as training data. The process is repeated until all observations have been used once in the validation data. Second, the laser estimates were compared with field estimates for 65 forest stands in the Swedish state forest (Sveaskog). In Sweden, forest management planning is conducted using forest stands; therefore, validation should also be performed standwise (Holmgren 2004). Forest variables are predicted by the fitted models for every grid cell of the area of interest. Cell estimates in turn are combined to stand estimates.

The accuracy was tested through the comparisons of the absolute and relative Root Mean Square Error (RMSE) and bias.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \tag{4}$$

$$RMSE\ (\%) = \frac{RMSE}{\bar{y}} 100 \tag{5}$$

$$Bias = \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)}{n} \tag{6}$$

$$Bias\ (\%) = \frac{Bias}{\bar{y}} 100 \tag{7}$$

Where $\hat{y}_i$ is the estimated value, y_i is the observed value, $\bar{y}$ is the arithmetic average of the observed values and *n* is the total number of plots or stands of the evaluation data.

Table 3: Forest variables and associated regression models used for local predictions by SLU in the beta version of the ALS-based national forest estimates released in spring of 2015

Variables	Linear Regression Model
Height (m ha^{-1})	$H_i = \beta_0 + \beta_1 P95 + \varepsilon_i$
Diameter (cm ha^{-1})	$D_i = \beta_0 + \beta_1 P80 + \beta_2 (P80 * VR) + \varepsilon_i$ $D_i = \beta_0 + \beta_1 P90 + \beta_2 (P90 * VR) + \varepsilon_i$ $D_i = \beta_0 + \beta_1 P80 + \beta_2 (P90 * VR) + \varepsilon_i$ $D_i = \beta_0 + \beta_1 P90 + \beta_2 (P80 * VR) + \varepsilon_i$
Basal Area (m^2 ha^{-1})	$BA_i = \beta_0 + \beta_1 (P90 * VR) + \varepsilon_i$ $BA_i = \beta_0 + \beta_1 (P80 * VR) + \varepsilon_i$
Volume (m^3 ha^{-1})	$\sqrt{V_i} = \beta_0 + \beta_1 P80 + \beta_2 (P90 * VR) + \varepsilon_i$ $\sqrt{V_i} = \beta_0 + \beta_1 P80 + \beta_2 (P80 * VR) + \varepsilon_i$ $\sqrt{V_i} = \beta_0 + \beta_1 P90 + \beta_2 (P90 * VR) + \varepsilon_i$ $\sqrt{V_i} = \beta_0 + \beta_1 P90 + \beta_2 (P80 * VR) + \varepsilon_i$

In these Models:

- β_0 , β_1, and β_2 are regression coefficients.
- *P95*: 95th percentile elevation i.e. the elevation below which 95 percent of the LiDAR points lie for a plot.

- *P90*: 90th percentile elevation i.e. the elevation below which 90 percent of the LiDAR points lie for a plot.
- *P80*: 80th percentile elevation i.e. the elevation below which 80 percent of the LiDAR points lie for a plot.
- *VR*: percentage of first returns over 1.5m above ground (number of first returns above 1.5m divided by the total number of first returns).

2.4 Model improvement for forest variables

A general regression model to estimate forest variables for a large region can be developed, but it is important to take into account that there are different aspects that may affect the quality of the model such as: geographic location, forest density, ecoregions, and distance from the water.

Tests were done in order to investigate whether the quality of the estimates for the four variables in question could be improved and if so, give indications about the different models. The development of regression models for the estimation were carried out following the previous steps; however, there was an analysis for selecting new explanatory variables. In regression analysis, the explanatory variable can be influenced by quantitative and qualitative variables. Quantitative variables are common and easily acquired. On the other hand, qualitative variables are not easy to obtain (Missio and Jacobi 2007). Qualitative variables can be very useful as a predictor, since they indicate the absence or presence of a quality or attribute. Thus, a method used to quantify these attributes is by building dummy variables. These variables assume only two values, commonly 0 and 1 (Missio and Jacobi 2007, Chatterjee and Hadi 2006). The values 0 and 1 indicate the presence or absence of an attribute.

Götaland's vegetation varies all over the region; for instance, closer to the coast tree heights are generally lower than within the region in general. With this in mind modelling was performed for height, volume, diameter and basal area. Tests with explanatory variables related to geographic position of the forest such as altitude, latitude and coastal vegetation were conducted. The information related to the coastal vegetation was extracted by the creation of dummy variables. Dummy variables were added to the basic models to investigate whether the estimates could be improved.

Dummy variables were created to distinguish the vegetation within a buffer zone of 20 km and 50 km from the coast. The variable altitude times latitude (*Alt*Lat*) was also tested. The altitude was calculated from the Swedish digital elevation model (DEM) obtained from the nationwide laser scanning. For the latitude, the northern coordinates recorded in the laser data were used.

Linear regression was performed and included the following dummy variables which provided information regarding proximity to the coast in the model:

$$coast\_20km = \begin{cases} 1, & if the\ plots\ are\ inside\ the 20km\ buffer\ zone \\ 0, & otherwise \end{cases}$$

$$coast\_50km = \begin{cases} 1, & if the\ plots\ are\ inside\ the\ 50km\ buffer\ zone \\ 0, & otherwise \end{cases}$$

Tests were performed by applying a two-step procedure. First, we identified the training dataset giving the more accurate results (only permanent plots or permanent plus temporary included). Next, we identified the models with the best performance considering the training set for each forest variable. Subsequently, we applied the two previously selected dummy variables (considering the buffer zone) and also tested the *alt*lat* variable by including it to these models.

The significance of the *dummy* variables was tested, through p-values, evaluating the contribution of these variables to the model. The models including the *dummy* variables were assessed in terms of R^2, RMSE and bias, identifying the effects of including *dummy* variables to the accuracy of the predictions.

3 Results

3.1 Comparison of regional and local models

The results in terms of RMSE and bias for forest stands predicted from local and regional calibration of the best models are shown in Table 4. The accuracy assessment on stand level of the regional estimates for *H, D, BA* and *V* are presented for the models which were calibrated with only permanent NFI plots. All explanatory variables had a significance level $p < 0.01$. The accuracy is identified in absolute and relative RMSE and bias. In general, a higher accuracy was observed when applying the local model as predictors of forest variables. For all variables validated, the RMSE and bias were slightly better for the local models, with the highest increase in RMSE for the predicted volume (3%) when applying the regional model. Both regional and local models presented negative bias for height and volume, indicating a trend of underestimation of these variables. On the other hand, biases for diameter and basal area were positive, indicating a slight overestimation of these variables by the model.

Table 4. Relative and absolute root mean square error (RMSE) and bias evaluated on stand level using Sveaskog stands for the forest variables estimated (*H*, *D*, *BA*, *V*) by: 1) local regression models trained with only permanent NFI plots; and 2) regional regression models trained with only permanent NFI plots

	Local models				Regional models			
	H ($m\ ha^{-1}$)	*D* ($cm\ ha^{-1}$)	*BA* ($m^2\ ha^{-1}$)	*V* ($m^3\ ha^{-1}$)	*H* ($m\ ha^{-1}$)	*D* ($cm\ ha^{-1}$)	*BA* ($m^2\ ha^{-1}$)	*V* ($m^3\ ha^{-1}$)
Mean	16.5	22.8	26.7	211.8	16.9	23.5	26.06	206.6
RMSE	1.6	2.7	3.7	35.5	1.7	3.2	3.9	42.2
RMSE%	8.8	11.8	14.0	15.9	9.7	13.8	14.7	18.8
Bias	-1.2	0.1	0.6	-10.8	-1.0	0.6	-0.2	-18.1
Bias%	-6.7	0.4	2.3	-4.9	-5.4	2.5	-0.6	-8.1

3.2 Permanent and temporary plot datasets

The results of the cross-validation accuracy assessment on plot level of the regional estimates for *H, D, BA* and *V* are presented for models which were calibrated with both permanent and temporary NFI plots and only permanent NFI plots in Table 5 and Table 6 respectively. All explanatory variables had a significance level $p < 0.01$. The accuracy is identified in RMSE and bias.

Among the models used by SLU for the estimation of the response variables *D, BA* and *V* the ones that had the best performance after calibration with training data containing only permanent NFI plots and with both permanent and temporary NFI plots are shown in equation 8, 9 and 10.

$$D_i = \beta_0 + \beta_1 P90 + \beta_2 (P80 * VR) + \varepsilon_i \quad (8)$$

$$BA_i = \beta_0 + \beta_1 (P90 * VR) + \varepsilon_i \quad (9)$$

$$\sqrt{V_i} = \beta_0 + \beta_1 P90 + \beta_2 (P80 * VR) + \varepsilon_i \quad (10)$$

For all forest variables, the models applying only permanent plots performed better than the models applying both permanent and temporary plots. The RMSE of permanent plots was smaller in all cases. Notably for basal area and volume, with RMSE more than 1% unit lower when applying only permanent plots. All models presented small negative bias; thus, lightly underestimating the forest variables.

Table 5. Regression model statistics (independent variables significances, adjusted R^2) and cross-validation results on plot level (absolute and relative RMSE and bias) for the estimation (*H, D, BA, V*) predicted using regional training dataset (493 NFI plots) including both permanent and temporary plots

Response variable	Explanatory variable	Coefficients	RMSE	RMSE%	Bias	Bias%	Adj R^2
H (m ha⁻¹)	Intercept	1.745	1.79	12.04	0.000	-0.001	0.88
	*P95****	0.877					
D (cm ha⁻¹)	Intercept	0.726	4.65	22.16	-0.001	-0.004	0.74
	*P90****	1.947					
	*P80VR****	-0.007					
BA (m² ha⁻¹)	intercept	5.011	5.01	22.22	0.000	-0.001	0.76
	*P90VR****	0.018					
V (m³ ha⁻¹)	Intercept	3.153	41.01	24.03	-2.46	-1.44	0.87
	*P90****	0.350					
	*P80VR****	0.005					

Significance codes: $p \leq 0.001$ '***' $0.001 < p \leq 0.01$ '**' $0.01 < p \leq 0.05$ '*'

Table 6. Regression model statistics (independent variables significances, adjusted R^2) and cross-validation results on plot level (absolute and relative RMSE and bias) for the estimation (*H, D, BA, V*) predicted using regional training dataset (267 NFI plots) including only permanent plots

Response variable	Explanatory variable	Coefficients	RMSE	RMSE%	Bias	Bias%	Adj R^2
H (m ha⁻¹)	Intercept	1.827	1.65	11.06	-0.001	-0.005	0.90
	*P95****	0.877					
D (cm ha⁻¹)	Intercept	0.751	4.53	21.49	-0.005	-0.023	0.75
	*P90****	2.084					
	*P80VR****	-0.009					
BA (m² ha⁻¹	intercept	5.980	4.71	20.92	0.000	-0.001	0.76
	*P90VR****	0.017					
V (m³ ha⁻¹)	Intercept	3.297	36.84	21.66	-2.02	-1.19	0.89
	*P90****	0.321					
	*P80VR****	0.005					

Significance codes: $p \leq 0.001$ '***' $0.001 < p \leq 0.01$ '**' $0.01 < p \leq 0.05$ '*'

H, D, BA and *V* estimation using the regression models built with only training data containing permanent plots (Table 6) showed the highest correlation (R^2) 0.90, 0.75, 0.76, and 0.89 respectively between predicted values and field measured values at a regional level. Cross-validation analysis by RMSE and bias shows that the use of permanent NFI plots for the calibration provides better accuracy for the models.

For the evaluation on stand level using the Sveaskog stands (Table 7), the forest variables *H* and *D* predicted with models trained with only permanent plots were slightly more accurate (respective RMSE% of 9.7% and 13.8%) than the ones predicted with models trained with both temporary and permanent plots. On the other hand, the predictions for *BA* and *V* by models trained with both temporary and permanent plots were slightly more accurate (respective RMSE% of 14% and 17.7%) than the ones predicted with models trained with only permanent plots.

Table 7.Relative and absolute root mean square error (RMSE) and bias evaluated on stand level using Sveaskog stands forest variables estimated (*H*, *D*, *BA*, *V*)by: 1) the regional regression models trained with permanent NFI plots (267 plots); and 2) the regional regression models trained with both permanent and temporary plots (493 plots)

	Training dataset							
	Permanent NFI plots				Permanent and temporary NFI plots			
	H (m ha^{-1})	*D* (cm ha^{-1})	*BA* (m^2 ha^{-1})	*V* (m^3 ha^{-1})	*H* (m ha^{-1})	*D* (cm ha^{-1})	*BA* (m^2 ha^{-1})	*V* (m^3 ha^{-1})
Mean	16.9	23.5	26.06	206.6	16.9	23.5	26.3	210.1
RMSE	1.7	3.2	3.9	42.2	1.7	3.2	3.8	39.7
RMSE%	9.7	13.8	14.7	18.8	9.8	14.0	14.0	17.7
Bias	-1.0	0.6	-0.2	-18.1	-1.0	0.6	0.1	-14.6
Bias%	-5.4	2.5	-0.6	-8.1	-5.5	2.7	0.2	-6.5

Differences between laser-estimated and field measured *H, D, BA* and *V* were plotted against field-measured values see Figure 6. In the residues distribution, it was observed a clear trend with high values generally underestimated for *H, D* and *BA* estimates. Volume shows slightly better distribution.

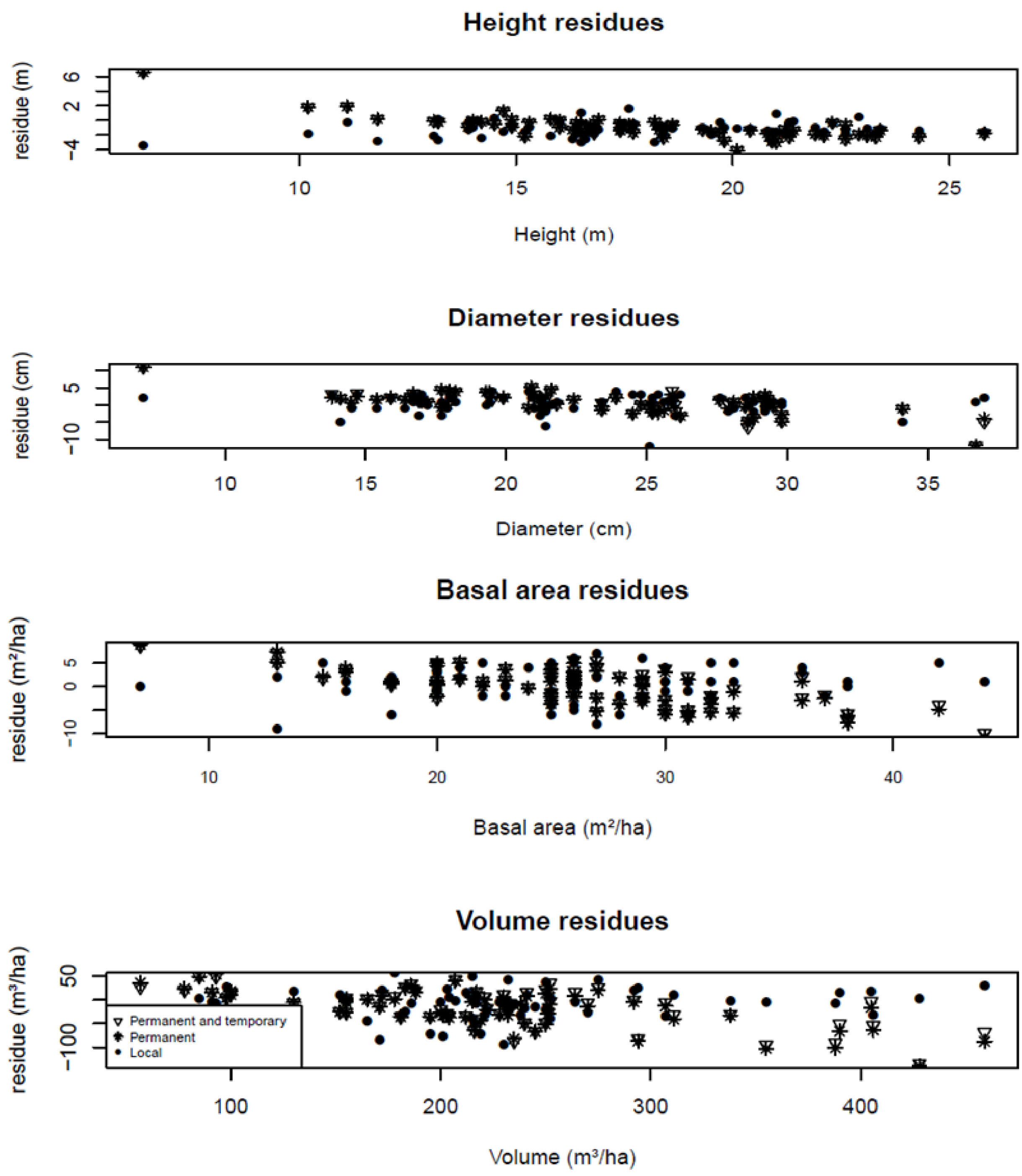

Figure 6. Laser-estimated *H*, *D*, *BA* and *V* using the regional regression models trained using only permanent NFI plots and both permanent plus temporary, as well as local regression models trained with permanent NFI plots plotted against the field-measured (*H*, *D*, *BA* and *V)* of the 65 Sveaskog stands.

3.3 Inclusion of dummy variables

Table 8 shows the cross-validation results on plot level of the regression analysis including the two *dummy* variables (coast_20km, coast_50km) and *alt*lat* as explanatory variables. The *alt*lat* variable was significant only for the diameter prediction. In general, this variable presented negative coefficients. The buffer zones of 20 and 50 km from the coast were significant for both diameter and basal area prediction. Both coefficients related to the buffer zone presented positive values. The coefficients from the 50 km buffer variable were smaller compared to the coefficients of the 20 km buffer variable.

The predictions for diameter and basal area slightly improved with the inclusion of the *dummy* variables. The RMSE% for diameter reduced from 21.49 to 21.15% with the inclusion of the coast_20km variable, with concurrent increase on the R^2 from 0.75 to 0.76. The same behaviour was observed for the basal area, however with a slighter improvement of the RMSE% from 20.92 to 20.83%.

Table 8.Regression model statistics (independent indicator variables significances, adjusted R^2) and cross-validation results on plot level (absolute and relative RMSE and bias) for estimates of forest variables when including dummy variables in the models calibrated with regional training dataset containing only permanent NFI plots (267)

Response variable	Explanatory variable	Coefficients	RMSE	RMSE%	Bias	Bias%	Adj R^2
	coast_20km**	1.845	4.46	21.15	-0.004	-0.022	0.76
D (cm ha^{-1})	coast_50km*	1.228	4.51	21.37	-0.004	-0.021	0.74
	alt_lat**	-0.019	4.48	21.27	-0.006	-0.027	0.76
	coast_20km*	1.498	4.68	20.77	0.000	-0.001	0.76
BA (m² ha^{-1})	coast_50km*	1.206	4.69	20.83	0.000	0.000	0.76
	alt_lat	-0.001	4.71	20.92	0.001	0.005	0.76

Significance codes: $p \leq 0.001$ ’***’ $0.001 < p \leq 0.01$ ’**’ $0.01 < p \leq 0.05$ ’*’

Validation on stand level (Table 9) shows that forest variables *D* and *BA* predicted with models derived using only permanent plots were slightly more accurate (respective RMSE% of 13, 13.5, 14.5 and 14.4%) once the *dummy* variables were included than the ones predicted without the inclusion of the *dummy*, which mean that the buffer zones of 20 and 50 km were significant for both variables.

Table 9.Relative and absolute root mean square error (RMSE) and bias evaluated on stand level using Sveaskog stands for the forest variables *D* and *BA* estimated including the dummies variables *Coast_20km* and *Coast_50km,* based on regional regression models trained with 267 permanent NFI plots

Response variable	RMSE	RMSE%	Bias	Bias%
*D*20 (cm ha^{-1})	2.99	13.0	0.30	1.3
*D*50 (cm ha^{-1})	3.09	13.5	0.51	2.2
*BA*20 (m^2 ha^{-1})	3.81	14.5	-0.44	-1.7
*BA*50 (m^2 ha^{-1})	3.79	14.4	-0.34	-1.3

4 Discussion

The study's purpose was to evaluate the possibility of using regional models to estimate forest variables of a given region of Sweden (Götaland) through the comparison between the calibration of regional and local models by using different training datasets. Area-based method and linear regression analysis were used. ALS data obtained from the nationwide laser scanning was combined with training data from the NFI to build the regression models.

4.1 Regional and local model comparison

The training dataset used for the calibration of the models for regional estimates was larger than the average for training dataset used for local models (300 plots) when both permanent and temporary plots (493 plots) were used. However, using only permanent plots reduced the dataset to 267 plots. The results showed better accuracy for the models calibrated at a local level. The methodology used for the local predictions presents uncertainty regarding the forecasting and back-casting of forest variables to the date they were laser scanned, since it might carry errors aggregated during the estimations, due to changes that might have occurred (e.g. clear cutting, thinning, etc.) in the time period between the field inventory and the laser scanning. The reason behind the better behaviour of the local predictions from local models might be related to higher number of plots per area unit, since the different forest characteristic might be better represented. Moreover, local models will better represent the local forest conditions. Thus, the stock is estimated more accurately than using a regional model. For instance the sampling intensity of the study area using only permanent plots was 1 plot per 19,827 ha, that is 267 permanent plots to calibrate a region of 5.3 million ha (Götaland area without Gotland province (166,000 ha), while including temporary plots expanded the sampling intensity to 1 plot per 10,738 ha. On the other hand, sampling intensity for local calibration was 1 plot per approximately 416.67 ha (125,000ha divided by 300 plots), however it is important to take into account that the plots used for calibration of the local models may also come from adjacent blocks. In addition, a major part of the permanent plots used in this study were geo-located with higher accuracy (1m) than the temporary plots (5m), thereby the variance between laser metrics and forest variables is lower; however permanent plots may give better estimates because the linking between laser metrics and field observations are less sensitive to positional errors if the plots are larger. In this context the use of local models is likely to be the most realistic way to obtain nationwide wall-to-wall estimates of forest resources, since the NFI plots are available for calibration of the models.

The number of permanent plots used for the regional model calibration was lower; however, it still provides comparable accuracy. With only 267 permanent plots the calibration of the regional models present satisfactory results. Today, remote sensing is still used as an auxiliary for forest inventory since field data is needed to calibrate the models. Nevertheless, this study shows that a small number of plots can potentially provide field data for a regional model.

The results of our estimations were comparable to the ones found in the literature. Hollaus et al. (2007) obtained R^2 of 0.85 and RMSE of 21.4%, estimating stand volume in mountainous regions in Austria. Lefsky et al. (2005) obtained RMSE ranging from 22.0 to 28.6% studying the application of ALS for predicting forest structure variables in the Pacific Northwest region of USA. Maltamo et al. (2011) predicted stand volume by applying ALS data with RMSE inferior to 15% and height estimations with RMSE ranging from 8 to 9%.

The lower accuracy of regional models might be expected when mapping larger regions, given that the conditions are more heterogeneous in terms of forest types and site characteristics. Furthermore, the site quality is a major factor affecting forest structure, e.g. height, volume, growth and biomass (Vanninen et al. 1996). Naesset and Gobakken (2008) pointed out this issue regarding the application of ALS for large regions. According to the authors, when modelling forest structure at large scales, it is essential to account for geographical characteristics and forest types, suggesting stratification and combining field plots with individual strata in order to overcome this concern.

Even though the regional models presented poorer accuracy, they still provided reasonable estimates, comparable to traditional forest inventory methods and other remote sensing techniques. In this context, the application of ALS data at regional scale, combined with NFI sample plot data present a great opportunity to successfully integrate the datasets, providing a cost-effective inventory system. Tuominen et al. (2014) assessed the applicability of NFI sample plot data with ALS in Finland. The results showed potential to integrate the NFI data in order to increase efficiency of the forest inventory; however, with recommendations for improving the sample design of NFI, to enhance the compatibility with the ALS dataset. Moreover, the predictions with similar levels of accuracy when applying the regional models provide the opportunity of reducing efforts on data acquisition and processing, when performing the forest inventory, therefore reducing costs.

4.2 Permanent and temporary plot datasets

We compared the model parameters when adjusted with permanent and permanent plus temporary plots. The use of the different datasets (only permanent or permanent plus temporary plots) had an impact on the volume model selection. In addition, the models fitted with only permanent plots generally presented better performance, compared to the model fitted using both temporary and permanent plots. The inclusion of temporary plots might increase the plot location error, resulting in a poorer performance. In this sense, the information regarding location of temporary plots is crucial in order to achieve suitable model performance which could improve if GPS with higher accuracy was used. Another factor that might have contributed to such result is that temporary plots are smaller than permanent plots (7m versus 10m radius), that is permanent plots cover larger areas.

4.3 Inclusion of indicator variables

The inclusion of *dummy* variables in forest models has been successfully applied in order to describe site characteristics, provenance, and geographic location, allowing improvement of estimations of forest structure, such as biomass, stand volume and tree height (Fu et al. 2012; Sunanda and Jayaramen 2006). In the models tested, the inclusion of *dummy* variables affected mainly the diameter and basal area estimates with no effect on volume. A possible explanation for this outcome is the phenomenon of greater diameter in closer proximity to the coast, whereas volume is not affected likely due to the shape of the trees. Closer to the coast the trees might have a more conic shape, thus even though the diameter is higher the volume is not. The buffer zones of 20 and 50 km were significant for the basal area and diameter models, with increasing diameter with proximity to the coast. The proximity to the coast has impact on the site characteristics of the stand as well. The microclimate, with lower temperature range near the coast, has positive impact on forest growth, promoting stands with larger average diameter and basal area. The inclusion of the *lat*alt* variable was significant only for diameter, with a negative coefficient; therefore, with decreasing diameter in northern and higher areas. This behaviour might be related to the temperature reduction and limited growth in northern areas.

Moreover, the inclusion of the *dummy* variables improved the model predictions for basal area and diameter, reducing the RMSE and increasing the R^2 for both models. Given the relatively simple acquisition of the information regarding the buffer zones around the coast, the inclusion of this information in the models is feasible. Therefore, it is possible to improve the predictions of forest inventories, allowing a more adequate planning of forest management.

5 Conclusions

Three conclusions may be drawn from the study. First, the regional models produced estimates of forest variables comparable to the ones produced using the local estimators. Although the number of NFI field plots was less for the regional models calibration, the models estimation still satisfy NFI precision criterion. Thus, there were no serious disadvantages with respect to the use of regional model estimators. Second, the models' accuracy improved if regional models were calibrated using only permanent NFI plots. Third, the buffer zones of 20 and 50 km were significant for the basal area and diameter models, with increasing diameter with proximity to the coast. Multiple advantages accrue with the use of regional models regression estimators. In particular, they are easier and faster to implement because selection of NFI plots occur only once; moreover, sample size requirements are more easily satisfied since there is no need for forecasting and back-casting field estimates.

6 Acknowledgements

First and foremost, I would like to humbly acknowledge my supervisor Mats Nilsson for his invaluable support and guidance to the completion of this endeavour. I wish to express my deep appreciation to the people and institutions that make the ERASMUS MUNDUS scholarship program a reality, and those who support the MSc European Forestry program, especially Marjoriitta Möttönen (UEF) and Diane Wästerlund (SLU) my coordinators. With their support, I had the unique opportunity to pursue my education in one of the most prestigious forestry programs in Europe.

I also extend my gratitude to the whole Department of Forest Resource and Management at SLU for the great academic, human and social environment, of co-operation and interaction, especially to Heather Reese for her priceless guidance; and to Mattias Nyström and Jonas Jonzén for their academic support at the Ljungbergslaboratoriet and for their insightful and interesting conversation. I also thank the Swedish NFI for providing field data. Last but not least, I would like to thank my family and friends. Their support and encouragement was crucial to my success.

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