

**Dissertationes Forestales 256**

Optical data-driven multi-source forest inventory  
setups for boreal and tropical forests

Eero Muinonen

School of Forest Sciences  
Faculty of Science and Forestry  
University of Eastern Finland

Academic dissertation

To be presented, with the permission of the Faculty of Science and Forestry of the University of Eastern Finland, for public examination in the auditorium BOR100, Borealis building on Joensuu campus of the University of Eastern Finland on Friday 5 October 2018 at noon (at 12 o'clock).

*Title of dissertation:* Optical data-driven multi-source forest inventory setups for boreal and tropical forests

*Author:* Eero Muinonen

*Dissertationes Forestales* 256

<https://doi.org/10.14214/df.256>

Use licence [CC BY-NC-ND 4.0](https://creativecommons.org/licenses/by-nc-nd/4.0/)

*Thesis supervisors:*

Professor Matti Maltamo

School of Forest Sciences, University of Eastern Finland, Joensuu, Finland

Docent Kalle Eerikäinen, D.Sc. (Agr. & For.), M.Sc. (Tech.)

School of Forest Sciences, University of Eastern Finland, Joensuu, Finland

*Pre-examiners:*

Docent Janne Heiskanen, Ph.D.

Department of Geosciences and Geography, University of Helsinki, Finland

Mait Lang, PhD

Tartu Observatory, Faculty of Science and Technology, University of Tartu, Tõravere, Estonia

*Opponent:*

Associate professor Mats Nilsson

Department of Forest Resource Management,

Swedish University of Agricultural Sciences, Umeå, Sweden

ISSN 1795-7389 (online)

ISBN 978-951-651-602-1 (pdf)

ISSN 2323-9220 (print)

ISBN 978-951-651-603-8 (paperback)

*Publishers:*

Finnish Society of Forest Science

Faculty of Agriculture and Forestry of the University of Helsinki

School of Forest Sciences of the University of Eastern Finland

*Editorial Office:*

Finnish Society of Forest Science

Viikinkaari 6, FI-00790 Helsinki, Finland

<http://www.dissertationesforestales.fi>

**Muironen, E.** (2018). Optical data-driven multi-source forest inventory setups for boreal and tropical forests. *Dissertationes Forestales* 256. 53 p.  
<https://doi.org/10.14214/df.256>

## **ABSTRACT**

The aim of the studies in this thesis was to apply and further develop methods in multi-source forest inventory tasks in boreal and tropical forests. The applications presented in this dissertation are based on optical remote sensing data and k-nearest neighbours techniques, both of which are common components in multi-source forest inventory.

The use of variograms as a texture information source in standwise volume estimation was tested using image data from a digitized aerial photograph taken in Hyytiälä, Finland. According to the leave one out cross-validation, the accuracy of volume estimation at stand level improved when empirical values of semivariance were included in the set of feature variables.

Landsat 5 Thematic Mapper (TM) satellite data was utilized in forest cover and volume mapping in Terai, Nepal. A corresponding multi-source forest inventory-oriented processing chain was also tested and demonstrated in forest volume mapping in the region of Kon Tum province in Vietnam. In these two studies, coarse scale MODIS reflectance products were used as a reference in a local correction approach conducted for the relative calibration of Landsat TM images.

Multi-source forest inventory techniques for obtaining biomass maps have facilitated the development of a spatially explicit methodology to estimate the bioenergy potentials of forest chips. The technical bioenergy potential of forest chips was calculated in a case study in Central Finland, based on the logging residues and stumps from final fellings.

An adaptation of the abovementioned methods and techniques in studies with target areas of forests in sub-tropical and tropical zones in Nepal and Vietnam was carried out using open source software tools. These studies serve the purpose of capacity building in utilizing remote sensing data in forest inventory activities related to the REDD+ mechanism, and estimating bioenergy potentials provides quantitative decision making support in the field of forest bioenergy production.

**Keywords:** k-nearest neighbours, satellite images, remote sensing, technical bioenergy potential, variogram, wall-to-wall maps.

## ACKNOWLEDGEMENTS

The research material of the first study was collected during a research project funded by the Finnish Ministry of Agriculture and Forestry. The first study was conducted in the University of Joensuu, Faculty of Forestry (involved in the University of Eastern Finland since 2010). Three later studies were carried out in the Finnish Forest Research Institute (Metla), i.e. the Natural Resources Institute Finland (Luke) since 2015. The ICI project in Metla was funded by the Ministry for Foreign Affairs of Finland, and together with counterparts in Finland, Vietnam and Nepal, it broadened my view of multi-source forest inventory in foreign countries. Further processing the output of the multi-source forest inventory was made possible through involvement with the research team of forest bioenergy in Metla. The University of Eastern Finland (School of Forest Sciences) supported me in writing this thesis summary.

I am very grateful to my supervisors, Professor Matti Maltamo and Dr Kalle Eerikäinen, who provided valuable comments and suggestions that were needed to finalize this thesis. In particular, Kalle Eerikäinen managed the ICI project, and his contribution as a co-author was essential in conducting the forest biometrical modelling. I thank all of my co-authors in Finland, Vietnam and Nepal for their contribution to these research articles. Jaakko Heinonen always found time to guide and help me when I was working in Metla, and always impressed me with his mathematical and statistical knowledge and patience. Juho Pitkänen compiled the basic calculation routines for the nearest neighbour approach that were used in Vietnam and Nepal. Heikki Parikka offered valuable technical and GIS guidance. I would also like to thank Dr Kari Korhonen and Dr Perttu Anttila for granting me the opportunity to work in their research groups in Metla. In the University of Eastern Finland, I would like to thank Professors Timo Tokola, Timo Pukkala and Heli Peltola for their encouragement towards writing this thesis summary. I wish to thank all the personnel involved in the collection of the field data used in these studies, and acknowledge the value and the hard work needed to plan and collect the field materials needed for forest research. I would also like to thank my research colleagues and friends for their comments and help in conducting this research, and for their company both 'on the road' and on the playing fields.

On a more personal note, I would like to thank my brothers Karri and Kalle for their company and the mind-refreshing conversations we have shared during our working weekends in our summer cottage in Sulkava. Finally, I would like to warmly thank my family at home. Satu has kept me alive with all of her love and healthy food. Antti, Valtteri, Miikka and Miro have always shown me the ways of the Force, and given me the New Hope I have needed in life – thank you all.

Joensuu, August 2018

Eero Muinonen

## LIST OF ORIGINAL ARTICLES

This dissertation is based on the following four articles, which are referred to by their Roman numerals in the text. The articles are reprinted with the kind permission of the publishers.

- I Muinonen E., Maltamo M., Hyppänen H., Vainikainen V. (2001). Forest stand characteristics estimation using a most similar neighbor approach and image spatial structure information. *Remote Sensing of Environment* 78(3): 223-228.  
[https://doi.org/10.1016/S0034-4257\(01\)00220-6](https://doi.org/10.1016/S0034-4257(01)00220-6)
- II Muinonen E., Parikka H., Pokharel Y., Shrestha S., Eerikäinen K. (2012). Utilizing a multi-source forest inventory technique, MODIS data and Landsat TM images in the production of forest cover and volume maps for the Terai physiographic zone in Nepal. *Remote Sensing* 4(12): 3920-3947.  
<https://doi.org/10.3390/rs4123920>
- III Muinonen E., Pitkänen J., Hung N. P., Tinh M. V., Eerikäinen K. (2014). Integrating multi-source data for a tropical forest inventory—a case study in the Kon Tum region, Vietnam. *Australian Forestry* 77(2): 92-104.  
<https://doi.org/10.1080/00049158.2014.924170>
- IV Muinonen E., Anttila P., Heinonen J., Mustonen J. (2013). Estimating the bioenergy potential of forest chips from final fellings in Central Finland based on biomass maps and spatially explicit constraints. *Silva Fennica* 47 (4) article id 1022. 22 p.  
<https://doi.org/10.14214/sf.1022>

In study I, Muinonen was responsible for writing the manuscript. Data analyses and estimation were conducted by Muinonen and Maltamo. Data preparations and feature calculation were carried out by Hyppänen and Vainikainen.

In study II, satellite data preparation, estimation and satellite image data analyses were carried out by Muinonen. Parikka coordinated the procurement of visual interpretation data and field plot data for the analyses together with Pokharel and Shrestha. Parikka also contributed to the analyses conducted for mapping the forest cover. The generalization of sample tree variables and the calculation of stand volumes in studies II and III were carried out by Eerikäinen, who was also responsible for the nonlinear mixed-effects (NLME) modelling of tree characteristics, management of the inventory project and field data collection. Manuscript II was jointly written by Muinonen and Eerikäinen. Eerikäinen wrote the appendix of the article in study II.

In study III, Muinonen was responsible for preparing image data for the analyses and was supported by Pitkänen, who consulted especially in the programming work needed for the estimation. Eerikäinen carried out the NLME modelling of tree characteristics and computed the plot-level forest variables. Muinonen carried out the satellite image-based estimations and analyses. The manuscript was written jointly by Muinonen and Eerikäinen. Hung and Tinh managed the field data collection and assisted in the data preparation.

In study IV, the calculations and manuscript preparation were jointly carried out by Muinonen and Anttila. Mustonen was responsible for the biomass estimation and satellite image analysis. Anttila guided the general computation of the bioenergy potentials and provided the forestry parameters. The statistical analyses conducted in study IV were guided by Heinonen.

## TABLE OF CONTENTS

<b>1 INTRODUCTION.....</b>	<b>7</b>
1.1 Forest inventory and the role of remote sensing .....	7
1.1.1 National forest inventory .....	7
1.1.2 Forest management inventory .....	9
1.1.3 Mapping forest cover and biomass .....	11
1.2 From resource mapping towards further analyses .....	12
1.3 Overview of workflow in multi-source forest inventory .....	14
1.3.1 Data procurement .....	14
1.3.2 Selecting parameters for nearest neighbour estimation .....	18
1.3.3 Estimating forest variables .....	18
1.4 Objectives.....	19
<b>2 MATERIALS.....</b>	<b>20</b>
2.1 Study areas and field data .....	20
2.2 Remote sensing data.....	21
2.3 Ancillary digital data.....	22
<b>3 METHODS .....</b>	<b>23</b>
3.1 Relative calibration of satellite images .....	23
3.2 Computing spectral features.....	24
3.3 Nearest neighbour techniques in the estimation of forest variables .....	25
3.4 Cross-validation and feature selection .....	26
3.5 Calculation procedure for the bioenergy potential of forest chips .....	28
<b>4 RESULTS.....</b>	<b>30</b>
4.1 Usability of information on variograms in image interpretation (I) .....	30
4.2 Mapping forest cover and volume in tropical forests using <i>k</i> -NN (II and III).....	31
4.3 Estimating the bioenergy potential of forest chips (IV) .....	32
<b>5 DISCUSSION .....</b>	<b>33</b>
5.1 Variograms and image texture .....	33
5.2 Satellite images in forest cover and volume mapping.....	35
5.3 Satellite images and analysing the bioenergy potential of forest chips .....	38
<b>6 CONCLUSIONS .....</b>	<b>40</b>

# 1 INTRODUCTION

## 1.1 Forest inventory and the role of remote sensing

### 1.1.1 National forest inventory

Forest inventories support forest policy makers, the forest industry and the private forestry sector in their forest planning and decision making-processes by providing objective information of forest resources. The aspects of sustainability – economic, social and ecological – represent common strategic goals to be taken into account in the use of forest resources. In the long run, forests as a renewable natural resource formed a keystone of the industrialization and social welfare development that occurred in Finland in the 1900s. As a tool for forest monitoring, national-level forest inventories have been carried out in Finland since the 1920s (Tomppo 1996; 2006; Tomppo et al. 1998; 2012). The use of forest resources has been a recent topic of active discussion in Finland because the emerging forest policy in EU member states will take into account the fact that forests act as carbon sinks. For example, for this reason, objective forest statistics at regional and national levels are still needed today.

In the National Forest Inventory (NFI) of Finland, the sampling design and plot- and stand-level measurements have changed over time to respond to contemporary requirements, and also to optimize the use of resources and information available (Tomppo 2006a). In large scale forest inventories, such as NFI sample surveys, the two logical components of a forest inventory system are: 1) a measurement system, and 2) a calculation system (see e.g. Pukkala 1994; Kilkki 1984; Kangas et al. 2011). The underlying element of the two components of the forest inventory system is a sample of field plots that is laid out over the target area(s) of the inventory. Variables describing the forest site characteristics and tree-level characteristics obtained by tally and sample trees are measured in the field.

Field sampling and measurements are limited by budget constraints, and need to be used in a cost-efficient manner, so a systematic cluster sample has tended to be applied. A calculation system is the component where sample tree measurements are imputed to tally trees to compute stand-level variables, and also to calculate results for the area. A planning system is where the results of an inventory are utilized for generating information on forest production possibilities and the consequences of alternative activities. A planning system feeds the decision maker with information on the necessary criteria for use in a decision support system, and so helps in the analysis leading towards reasoned decisions. Besides the size of the given target area, factors like the time horizon and the strategic, tactical or operational levels of planning also set specific requirements for the calculation system.

Aerial photographs were already being utilized in the 5<sup>th</sup> (1964–1970), 6<sup>th</sup> (1971–1976) and 7<sup>th</sup> (1977–1984) Finnish NFIs in Northern Finland. Two-phase stratified sampling (stratification based on aerial photographs) was employed in the 5<sup>th</sup> and 6<sup>th</sup> inventories, and photo interpretation plots featured in the 7<sup>th</sup> inventory (see Tomppo 2006a p.180; Korhonen et al. 2013; see also Poso and Kujala 1971, Poso 1972 and Mattila 1985 as cited by Tomppo 2006a). When satellite remote sensing images became available in the late 1980s, Kilkki and Päivinen (1987) came up with an idea of utilizing remote sensing technology in the NFI of Finland and suggested a methodology to combine the existing field plot data of Finnish NFIs with satellite data, for obtaining reliable forest estimates by smaller regions than was possible with field plots only. In Finland, this meant aiming to produce results at a municipality-level,

whereas field plot-based results were accurate enough when compiled by Forestry Centres. Assuming that similar forest exists also around the target area of the inventory, then satellite image data could be used in creating a method of reference sample plots, closely related to the grouping method of Poso (1972 as cited by Kilkki and Päivinen 1987). Methodological tests of the technique were made using Landsat MSS, Landsat TM and SPOT HRV imagery, together with field data that was available from NFI7 and NFI8 (Muinonen and Tokola 1990; Tokola et al. 1996; Tokola and Heikkilä 1997). From that time, the underlying approach of nearest neighbours (NN) techniques was further developed at the former Finnish Forest Research Institute (known as the Natural Resource Institute since 2015), and this was finally tuned into a sophisticated calculation system, i.e. the non-parametric  $k$ -nearest neighbour ( $k$ -NN) estimation method, that has become a well-known method and widely applied in the field of satellite image-based forest inventory (e.g. Tomppo 1996).

A Finnish Multi-source NFI (MSNFI), (Tomppo et al. 1998; 2012; Katila and Tomppo 2001; Tomppo 2006b; McRoberts and Tomppo 2007; Tomppo et al. 2008a; for an improved version see, e.g., Tomppo and Halme 2004; Tomppo et al. 2009a; 2009b) is based on the  $k$ -NN method. In MSNFI, multiple map data sources have been utilized for separating areas of land use categories other than forest land, for example agricultural land areas, urban areas, buildings and roads (Tomppo et al. 1998). Techniques to reduce the effects of map errors have been presented by Katila et al. (2000), and Katila and Tomppo (2002).

NN techniques such as  $k$ -NN allow for estimating all of the forest variables simultaneously for a target element, usually in the form of a raster cell (a pixel in a satellite image). The approach is easily implemented (McRoberts 2008), and the covariance structure among the variables is also preserved (Tomppo et al. 1998). NN techniques have become widely used in forestry applications also in other Nordic countries (for a review of studies, see Tomppo et al. 2008b; 2009a; 2012), and the performance of the  $k$ -NN approach has been evaluated by e.g. Franco-Lopez et al. (2001) and Pachana (2016).

McRoberts and Tomppo (2007) discussed the remote sensing support for modern NFIs and noted that regardless of the quality of the estimates obtained using data from active sensors, remote sensing measurement of plots is not expected to completely replace field measurement any time in the near future. Studies using data from active sensors had been lacking the spatial extent required for NFIs, and did not adequately take into account the complexity of forest conditions. It was concluded at the time, that satellite imagery had contributed greatly to the ability of NFIs to produce more timely, cost efficient and precise inventory estimates, and had greatly facilitated the construction of spatial products that were in increasing demand. A further conclusion was that the use of digital remote sensing data of different spatial and spectral resolutions could be expected to become an essential part of large area forest inventories. As such, the availability of data and the development of statistically sound methods would be important factors for future development.

Næsset et al. (2013b) also note that for larger geographical regions such as counties, states or nations, it is not feasible to collect airborne Light Detection and Ranging (LiDAR) data, i.e. data acquired from Airborne Laser Scanning (ALS), continuously (“wall-to-wall”) over the entire area of interest. Thus, optical satellite images such as those provided by Landsat or SPOT, with a resolution of 10–30 m and with a large area coverage in a single image, still offer an alternative ancillary data source. The usability and potential of satellite images in data procurement for a planning phase has been reviewed by Mäkelä et al. (2011). Mirrored with past studies and the summary of McRoberts and Tomppo (2007), the availability and cost efficiency of satellite image data, together with a straightforward and easy-to-implement approach such as the  $k$ -NN technique are still applicable tools for NFIs. However, despite



their integration with new data such as ALS data being a most probable development scenario, this is strongly dependent on the availability of data (including satellite images) with different spatial and spectral resolutions.

### 1.1.2 Forest management inventory

In Finland and several other countries, although NFIs are conducted at national and regional levels, forest management inventories (FMI) are carried out at farm levels for private forests, and up to the level of target regions for tactical and operational forest planning for forest companies. Moreover, an NFI sample for a large area is too sparse for estimating reliable results by smaller areas, i.e. areas smaller than 200 000 ha (see Metsätieto 2015), such as a municipality or village. The operational unit in forestry in Finland comprises a forest stand – or a compartment –, so the sample-based inventory system is unable to support the spatially explicit data needed for tactical forest planning. Traditionally, aerial photographs have been actively utilized in stand delineation and assisting with field work. In FMI, field work has been carried out as a visual compartment level field survey supported with plot measurements (Koivuniemi and Korhonen 2006; see Maltamo and Packalen 2014). Stand-level treatment proposals could be mapped, and in this way assist the tactical forest planning with a spatially continuous forest stand dataset and stand-level forest attribute table. However, aerial digital cameras and computing capacity have developed to a level that allows the production of mosaicked digital aerial images. Remote sensing therefore offers the means to assess a spatially continuous image of the forest area.

The utility of the  $k$ -NN method in estimating stand-level means of stem density (trees/ha) and basal area ( $\text{m}^2/\text{ha}$ ) has been examined by McRoberts (2008), who also presented modifications to  $k$ -NN suited for a stand-level approach. The stand-level estimation was based on the averages of pixel-level predictions in a stand, and the modifications included inspecting the distribution of stem number and basal area for reference pixels over all of the stand target pixels in a locally (per target stand) adaptable manner. This partly corresponded to the method previously described by Malinen (2003). Additionally, covariates were sought using a genetic algorithm-based technique adapted from the procedure presented by Tomppo and Halme (2004). McRoberts (2008) concluded that the combination of strategic inventory data, TM imagery and NN techniques may provide an inexpensive and easily implemented alternative to expensive, sample-based management inventories, and that further research would be necessary that involved other forest types and plot types.

It has been noted in Finland that poor plot-level accuracy (a large RMSE at the plot-level) is limiting the performance of satellite image data in applications aiming to support stand-level forest management decisions. Accuracy results have been reported by e.g. Tokola et al. (1996) and Mäkelä and Pekkarinen (2001). In their study, Tokola et al. (1996) noted that the size of field plots defined by the relascope basal area factor of  $2 \text{ m}^2/\text{ha}^{-1}$  used in the Finnish NFI was too small when compared to the pixel size in nearest neighbour estimation, and was therefore causing extra variation to the relationship between the field and spectral data. A prerequisite for the use of small plots is their exact location in the field, and the geometric correction of the satellite material. A multi-criteria approach for reducing plot location error in assigning image pixel data to the field plot was thereafter developed with successful results by Halme and Tomppo (2001).

ALS has now proven to be well-suited for the estimation of standwise forest characteristics and the delineation of forest stands, and the development of forest applications originated in Norway (Næsset 2014) and Finland (Maltamo and Packalen 2014). The

underlying implementation requires a so-called area-based approach (Næsset 2014; Maltamo and Packalen 2014), where ALS point data-based explanatory features are computed in grid cells, each of which composes an estimation area unit (a unit size of 16 m × 16 m has been used in Finland). Ground truth data in the operational planning inventory comprises a set of circular field sample plots (Maltamo and Packalen 2014; Metsätieto 2015). Combining ALS and optical data from a digital aerial photograph can improve the tree species-specific estimates of growing stock volume (Packalén et al. 2009). Also, stand boundaries can be detected from an ALS data-based canopy height model (Mustonen et al. 2008), and stand-level predictions are aggregated from the grid cells that fall inside stand boundaries.

Forest attributes by grid cell are commonly predicted either via regression modelling or by utilizing the NN imputation, and are the main approaches applied in Norway and Finland respectively (see Næsset 2014; Maltamo and Packalen 2014). The ALS data-based methodology applied in forest management inventory in Finland has been widely based on NN estimation, namely the *k* Most Similar Neighbour approach (*k*-MSN), in which the similarity measure is built on the canonical correlation analysis between two groups of variables, i.e. the groups for design attributes and indicator attributes (Moeur and Stage 1995). Forest variables act as response variables, and the image data-based or ALS point data-based features act as feature variables, respectively (see McRoberts 2012). It is then possible to have a similarity measure accounting for several forest characteristics simultaneously. The initial motivation in the approach by Moeur and Stage (1995) was to impute missing observations in the data in a way that resembles true correlations occurring in the original data. In the *k*-MSN, NN estimation is applied, with the similarity measure corresponding to the distance function (Malinen 2003; Malinen et al. 2001; Packalén et al. 2009), and inverse distance weighting can then be applied for producing the weights of the neighbours.

To fulfil the requirements of species-specific stand attributes in Finland, combining ALS data with the spectral features from airborne images has proven successful (Maltamo and Packalen 2014). In the two-stage approach developed by Packalén et al. (2009), each ALS point is furnished by the spectral features from aerial photographs, where unrectified images are utilized instead of orthorectified images, and the overlap in aerial imagery allows an ALS point to be linked to several aerial image DNs (digital numbers). With this data set, ALS points can be classified by common tree species, and the approach was seen as preferable compared to using ALS data alone in aiming for tree species-wise volume estimates, which is the main objective in Finland.

Forest variables describing the stand-level growing stock can be estimated using ALS point cloud data and field plot data, resulting in an estimation quality fulfilling the needs of forest planning purposes. Therefore, ALS has established its place in FMIs in Finland. In a review of the development of Norwegian operational ALS forestry applications by Næsset (2014), forest stand characteristics such as tree size distributions and biomass quantification categorised by tree species were recognized as interests for up-coming development work. The review also mentioned that the evaluation of the performance of ALS data in combination with optical aerial images will continue. The combination of different data sources – also including multispectral LiDAR technologies (Hopkinson et al. 2016) – can offer a range of possibilities for future multi-source ALS forest inventory applications (Valbuena 2014).

### 1.1.3 Mapping forest cover and biomass

Forest above-ground biomass (AGB) is a key variable for the characterization of the forest state and its disturbance status, as well tracking its dynamics over time (Häme et al. 2013b). The Tier approach introduced by the Intergovernmental Panel on Climate Change (IPCC) has been used to describe levels of methodological quality and complexity in the measurement reporting and verification (MRV) assessment system (see Tokola 2015). In this way, the United Nations Framework Convention on Climate Change (UNFCCC) policy on Reduced Emissions from Deforestation and forest Degradation (REDD+) has provided guidelines to assist countries in developing carbon assessment methodologies (e.g. Asner 2009; Tokola 2015). For estimating aboveground carbon in the REDD+ monitoring setups, calculation chains are conventionally implemented using coefficients such as the biomass expansion factors discussed by Tokola (2015). Notably, Tokola (2015) emphasised that remote sensing-based applications are definitively key tools for REDD+ MRV, and the good practices applied in traditional forest inventories (such as a proper sample and fieldwork design) ought to be followed in allocating field plots and carrying out field measurements also in tropical conditions (see Olofsson et al. 2014).

The challenges in the fields of forest degradation and the REDD+ framework have been discussed, for instance by Morales-Barquero et al. (2014: see also Peres et al. 2006). In order to evaluate the possible reduction in greenhouse gas emissions for both deforestation and forest degradation, a baseline is required (Morales-Barquero et al. 2014). However, there is a lack of historical data on carbon stocks, and one needs to build concepts for separating between degradation and deforestation, and also the natural causes of fluctuation, so these introduce elements of uncertainty into the baseline determination process. Morales-Barquero et al. (2014) also mention that degradation is a process that is best assessed at the landscape level, because tropical forests are characterised by different stages of forest transition, due to both natural processes and impacts caused by human activities. Therefore, one should assess the overall carbon budget of each coherent landscape/management unit, and not individual patches of forest within the unit, in order to average out the temporary losses and gains. Morales-Barquero et al. (2014) also state that optical remote sensing faces a fundamental problem, in that changes in canopy cover are not a direct measure of the total biomass or of the degradation that is occurring below the canopy surface-level (e.g. fuelwood collection or grazing).

The role of LiDAR is to provide a ground truth type of information over large areas. The innermost REDD+ concept still lies in the realm of forest inventory (Tokola 2015). A review of approaches for LiDAR sampling over large areas was presented by Wulder et al. (2012, see p. 207), and it is noted that an evident way to generate measures in support of REDD+ programs is through the integration of optical imagery and samples of LiDAR data. Hou et al. (2011) and Tokola (2015) have underlined that only the upper parts of the canopy are detected and quantified using optical images, and this affects their use and applicability for the estimation of forest biomass. Unlike other remote sensing techniques such as optical remote sensing and Synthetic Aperture Radar (SAR), LiDAR does not suffer from the saturation problems associated with large biomass values. In addition, optical remotely sensed imagery and other spatial data can be used to aid stratification, to inform sampling, and also to enhance estimation (Wulder et al. 2012; see GOFCC GOLD 2016, section 2.10.2.2). In a further paper, several image sources were combined by Häme et al. (2013a) in mapping tropical forest classes. LiDAR data can be used to provide conventional sampling-based

estimates of biomass characteristics, and also to determine changes in the amount of biomass over time (GOFC-GOLD 2016; see also Asner 2009, Næsset et al. 2013a).

McRoberts et al. (2015) discovered that: 1) airborne laser scanning data has substantial utility for increasing the precision of forest AGB estimates, and 2) the  $k$ -NN technique is an effective method for predicting forest AGB from a combination of forest inventory and airborne laser scanning data. However, Drake et al. (2003) had previously concluded that it will probably be necessary to develop a series of relationships between LiDAR metrics and above-ground biomass in different bioclimatic life zones. The importance of climatic variables for developing general algorithms for the estimation of above-ground biomass in different tropical areas using LiDAR data was emphasized to be a focus of further study.

## 1.2 From resource mapping towards further analyses

In offering a large-scale example, the Finnish NFI field sample has provided the data source for a forestry scenario model developed for timber production analyses at national or regional levels (Siitonen et al. 1996; Hirvelä et al. 2017). In this, the two components of the MELA system are an automated stand simulator based on calculations conducted at tree-level, and an optimization package based on linear programming (Lappi 1992). Timber production analyses at regional level by forest centres can be based on the NFI field sample itself, where calculation units are generated by grouping the field plots based on plot-level and tree-level measurements. This linkage between the NFI measurement and the MELA forestry model has ensured versatile strategic analyses, used for instance in assessing sustainable production level possibilities. Ecological and social sustainability can also be taken into account in these calculations by way of the constraints imposed for instructing the feasibility of forest operations in terms of the input materials, or the constraints imposed as part of the optimization strategy.

Mäkelä et al. (2011) investigated the potential of multi-source methodology and satellite imagery in assisting the forestry scenario analysis using the MELA forestry model. In their study, the approach was based on Finnish NFI field data (i.e. image segmentation combined with  $k$ -NN estimation), and yielded promising results in estimating data for local scenario analyses. However, they stated that the accuracy of the satellite image-based estimation of forest stand variables is not accurate enough to support operational forest planning, mainly because of the mean stand size is less than 2 ha in Finland. Therefore, the interest in using satellite images has tended to be directed towards the strategic analysis of forest production possibilities (Mäkelä et al. 2011; see also Bååth et al. 2002).

Questions can be asked in the field of remote sensing forestry applications about how to fit the raster map representations of a set of forest variables and the planning view together, in a way that would best serve the needs of planning levels selected. It is worth keeping in mind the accuracy (RMSE) of satellite data-based estimation, e.g. ca. 60–80 % for total volume of growing stock at the pixel level, and ca. 40–60 % at the forest stand level when Landsat data is used (see Mäkelä 2011). Hou et al. (2011) tested ALOS AVNIR-2 optical satellite data in a tropical forest region in the Lao People's Democratic Republic, and discovered that in multiple regression estimation, the RMSE for stand volume was ca. 69 %. ALS data is an alternative to satisfy needs demanding better accuracy, whereas if the cost-effectiveness is taken into consideration, ALOS AVNIR-2 data is of potential to be used for rough but economic estimates of tropical forest attributes (Hou et al. 2011).

Bio-energy is seen as one of the key options to mitigate greenhouse gas emissions and substitute fossil fuels (Faaij 2006). Batidzirai et al. (2012) published a methodological review that also discussed the terminologies and analysed approaches used in estimating bioenergy potentials. The three types of potentials are summarized as follows: (i) theoretical potential describes the maximum amount of biomass that can be considered as theoretically available; (ii) technical potential describes the fraction of the theoretical potential that is available using current technological possibilities; and (iii) market (or economic) potential describes the share of the technical potential that meets economic criteria within given conditions. Furthermore, the fraction of technical potential is referred to as ecologically sustainable potential if restrictions related to environmental criteria such as nature conservation and soil/water/biodiversity preservation are also considered. Batidzirai et al. (2012) noted that there is an overlap between market potential and ecological potential, due to the fact that a share of ecological potential might not meet economic criteria and vice versa. Implementation potential is a variant of the economic potential that can be implemented within a certain time frame and under concrete socio-political framework conditions, including economic, institutional and social constraints and policy incentives. Several combinations can also be implicitly or explicitly analysed i.e. theoretical–technical and economic–implementation potentials (Batidzirai et al. 2012), or ecological–economical potentials (Smeets and Faaij 2007).

Guidelines for a reasonable framework in biomass resource assessment and analysis have been compiled by Vis et al. (2010), whose work aimed at harmonizing the use of terms and concepts within the scope of European work. Vis et al. (2010) divided the different biomass types into four biomass categories: Forest biomass and forestry residues, energy crops, agricultural residues, and organic waste. Furthermore, forest biomass includes several types of raw woody materials derived from forests or from the processing of timber, that can be used for energy generation. Thus, Vis et al. (2010) refer to a main-type (e.g. Forestry) and a sub-type (e.g. Primary forestry residue) to address the leftovers from harvesting activities such as twigs, branches, stumps etc. In the framework they present, the availability of forestry residues and waste is an underlying element in a working step for the ‘Estimation of biomass technical potentials’, illustrating the basic role in forests and the forestry sector, and the need of forest resource data to support further working steps. It can be noted that Vis et al. (2010) categorised potentials as types of theoretical, technical, economic and implementation potential – and lastly as a sustainable implementation potential. This being the case, it is important that both methodologies and influential factors are accounted for and documented when results are presented. Vis et al. (2010) also discuss that besides theoretical, technical, economic and implementation potentials, the fifth type (i.e. the sustainable implementation potential) is not a potential on its own, but rather the result of integrating environmental, economic and social sustainability criteria in biomass resource assessments. In this way, the sustainability criteria act like a filter on the theoretical, technical, economic and implementation potentials, leading ultimately to a sustainable implementation potential.

The methodologies used to assess biomass resources are generally categorised as (i) resource-focused, (ii) demand driven, or (iii) integrated approaches (Vis et al. 2010). In demand driven approaches, the competitiveness of biomass-based energy systems is compared with other options, whereas information from the models of different sectors (economic, energy, land use and climate) is integrated into the analysis in integrated approaches. In a resource-focused approach, the bioenergy resource and the competition between different uses of the resources are investigated, with a focus on the supply of biomass for bioenergy. Statistical and spatially explicit methods can also be distinguished under this

approach. Statistical methods combine statistical data and various conversion factors that are based on expert judgements, field studies and literature reviews. Spatially explicit methods take into account various location specific factors that affect the availability of biomass.

Spatially explicit methods present biomass availability in a location specific, or e.g. in a two-dimensional way on maps (Vis et al. 2010). Batidzirai et al. (2012) also noted that compared to statistical analyses, spatially explicit analyses are more suitable to reflect the impact of local or regional circumstances by combining the available spatially explicit data on land use. In a larger context, a multi-source inventory can serve as a logical platform for generating information for the analysis of bioenergy potentials at regional and national levels (Vis et al. 2010; Wohletz 2011). Moreover, remote sensing has been benchmarked in the approaches of both the REDD+ guided methodologies of developing countries, and also in developed countries for finding a sustainable level for the use of bioenergy as a renewable energy source in mitigating climate change, or in assisting forest management inventories, especially with regard to a spatial coverage of high resolution remote sensing data or ALS point data.

### 1.3 Overview of workflow in multi-source forest inventory

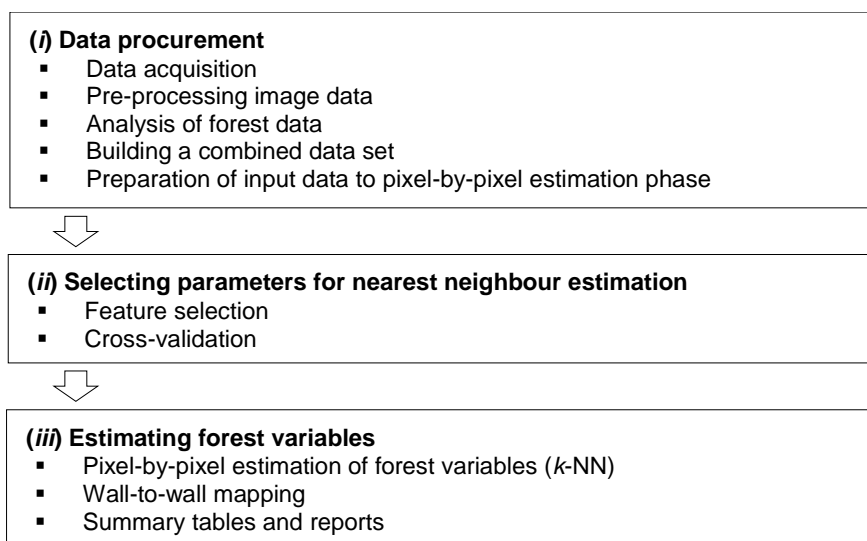
A forest inventory framework based on remote sensing can be categorised as a multi-source framework, especially when existing map data from several sources are combined in a GIS - platform to aid the estimation of forest attributes in the area of interest. This overview covers applications based on optical image data – mainly satellite data – and the NN estimation technique, i.e. the airborne or ALS data-specific elements are left out or only briefly mentioned, as is also the case for issues about analysing the reliability of the large area estimates or coverage of optional post-processing steps.

A general workflow of a multi-source forest inventory approach comprises identifiable working phases with different tasks (Figure 1). The workflow can be categorised into three thematic phases: (i) Data procurement, (ii) Selecting parameters for NN estimation, and (iii) Estimating forest variables. The reporting phase is hereby included in the last phase, since some input elements for reporting are calculated on-the-fly during the pixel-by-pixel estimation of forest variables. Moreover, the reports task in phase (iii) also covers the reliability analyses of the results at large area level.

#### 1.3.1 Data procurement

In the data procurement phase (see Figure 1), both image and mapped data are imported into the GIS database, and image data to be used in the mapping is pre-processed. In addition, managing and analysing field data is necessarily undertaken in this first phase of the process.

Available *digital map data* is utilized in separating some categories of non-forestry land (such as roads, buildings and agricultural areas) from further analysis and is usually implemented by using masks built from the auxiliary data (Tomppo et al. 1998). Changes in the landscape may also create a need to correct older map data. The timeliness of map data vs. other data sources is important to reduce map errors. Applying the pixel-by-pixel estimation by strata is a technique that reduces the effects of these map errors (Katila and Tomppo 2002). Ancillary data should provide continuous cover, i.e. a wall-to-wall raster map or a vector map that can be transformed into raster format. Once overlaid on the image data,



**Figure 1.** A schematic workflow in a multi-source forest inventory approach.

it acts as a mask showing pixels in the area of interest. It is also used in the stratification of sample units (pixels) and field plots.

In the absence of map data, another option could be e.g. the delineation of forest and non-forest land use classes, using image interpretation procedures such as the NN methods applied by Haapanen et al. (2004). However, the feasibility of the methodology needs to be investigated in each case. In this scenario, the estimated land use class from the image interpretation is then used to mask out non-forest -pixels. Other data sources may include a digital elevation model and boundaries of administrative regions or vegetation zones.

*Field data* in large regions is often collected using a systematic sample of field plots, as in the case of NFIs (e.g. Tomppo et al. 1998). Acquiring accurate field plot positions is an important issue, and exact map coordinates are needed to successfully furnish the field plots with spectral variables (Halme and Tomppo 2001). Another important task is the analysis of forest data in a calculation system (Figure 1), including modelling and imputing tree characteristics such as tree height and stem volume, and also calculating plot-level results. For usage in stratification and as ground truth in estimation, a combined data set is built and maintained, consisting of the field plots which are furnished with image spectral variables and ancillary data variables (Figure 1). In multi-phase sampling applications, a visual interpretation of an attribute such as a land use class can be incorporated into this data set.

*Optical remote sensing materials* are images taken using passive instruments, such as airborne cameras or spaceborne satellite sensors, that observe reflected solar radiation. Optical sensors operate primarily in the visible and infrared (ca. 0.4–15.0  $\mu\text{m}$ ) portions of the electromagnetic spectrum, whereas radar sensors operate in the microwave region (ca. 3–70 cm) (GOFC-GOLD 2016, section 2.10.4.1). Multispectral images contain measurements from multiple wavelength bands (channels) corresponding to reflected energy in different wavelengths. Images and sensors are commonly categorised based on resolution. In remotely

sensed imagery, resolution is significant in four measurement dimensions: spectral, spatial, radiometric and temporal (USGS Landsat Missions 2017). Spectral resolution is determined by the position in the spectrum, width and number of spectral bands, and these are factors that make up the degree of which individual targets can be discriminated on the multispectral image (Mather 1987). Spatial resolution is a measure of the amount of detail that can be seen in an image, and relates to the area on the ground that an imaging system (such as a satellite sensor) can distinguish (USGS Landsat Missions 2017). Radiometric resolution refers to the number of digital levels used to express the data collected by the sensor. Temporal resolution refers to the time that elapses between successive acquisitions of imagery (Mather 1987).

Spatial resolution has been used to categorise image materials. Imagery with a spatial resolution of less than 1 m has been considered as having a very high spatial resolution (VHSR), while correspondingly a high spatial resolution (HSR) imagery has a spatial resolution of less than 10 m, (see Olofsson et al. 2014). GOF-C-GOLD (2016) contains a review of the optical sensors available for monitoring deforestation, and uses categories of “Coarse” (250–1000 m), “Medium” (10–60 m), “Fine” (< 5 m) and “Very Fine” (< 1 m) resolution. Several systems have different spatial resolutions among their various spectral bands.

In their review, Lillesand et al. (2015, p.340) referred to “moderate resolution” as having a range from 4 to 60 m and “high resolution” as a resolution of less than 4 m, and noted the 4 m boundary was arbitrary. They also suggested that the evolution of land-oriented optical remote sensing satellite systems could be characterized by three general time periods: (1) the Landsat and SPOT “heritage” period when these systems completely dominated civilian remote sensing from space, (2) the immediate “follow-on” period (approximately between 1988–1999) when several other moderate resolution systems came into existence, and (3) the period since 1999, wherein both “high resolution” and “moderate resolution” systems have served as complementary sources. This latter period has also included the development of space borne hyperspectral sensing systems.

As mentioned earlier, Landsat TM and SPOT HRV images have been common imagery sources in forestry applications. Other possible sources include sources such as RapidEye satellites (6.5 m-resolution), and Sentinel-2 MSI (10 – 60 m resolution, dependent on the particular spectral band) which is one of the missions in the Sentinel Program of the European Space Agency (ESA). The Earth Observing System (EOS) program is conducted by NASA and features numerous satellite missions. Terra and Aqua spacecraft are platforms in this EOS program, and they both carry multiple instruments. Both Terra and Aqua carry a Moderate Resolution Imaging Spectro-Radiometer (MODIS). MODIS has a resolution of 250, 500 or 1000 m depending on wavelength and a swath width of 2230 km. In addition, compared to some earlier systems MODIS data is characterized by improved geometric rectification and radiometric calibration (Lillesand et al. 2015). The Landsat mission is also continuing, with the Landsat 8 launched in 2013 and Landsat 9 planned for 2020. Landsat Level-1 data can be searched and downloaded without charge (USGS Landsat Missions 2017).

Contrary to the case with moderate resolution systems, the operators of high-resolution satellite sensors have been and will continue to be commercial firms. The first four high-resolution systems were three managed by U.S.-based firms (IKONOS, QuickBird and OrbView-3) and one system operated by a company from Israel (EROS-A) (Lillesand et al. 2015). The SPOT-5 satellite was in action between 5/2002 and 3/2015, carrying 2 instruments (HRG) having multispectral bands with a resolution of 10 m, and 5 m for panchromatic bands. Even higher 2.5 m resolution for panchromatic bands could be accessed in SPOT-5



by combining scenes. Sensors in the satellites SPOT-6 and SPOT-7 (launched in 2012 and 2014 respectively) have a 6 m resolution in multispectral bands (blue, green, red, near-infrared) and a 1.5 m resolution in a panchromatic band (Lillesand et al. 2015; Satellite Imaging Corporation 2017).

Airborne images, such as those taken by using airborne digital cameras (or digitized aerial photographs earlier), offer an alternative to having a resolution of less than 1 m. This enables the observation of single trees and delineating forest stand borders with a high enough quality needed for operational forestry operations. Before the advent of digital airborne cameras, analogue aerial photographs were converted into digital form using a digital scanning instrument. Coarse spatial resolutions (e.g. 30 meters) make stand delineation in the image suffer from mixed pixels containing spectral signatures from nearby stands, compared to core pixels that carry signatures from one stand only. Higher-resolution images or ALS data enable texture features to be utilized (Haralick et al. 1973), and single trees can be detected in the image.

Satellite image pre-processing (Figure 1) includes corrections for atmospheric effect and topography, for instance. Building a data set by combining several nearby images into a mosaic can require some relative calibration due to different image conditions. In the case of using optical image data, radiometric corrections for atmospheric effects or reducing topographic effects from slope and aspect vs sun illumination can also be performed if necessary. From a user's point of view, other common needs are to rectify the original image with map data into a certain geographical coordinate system (i.e. georeferencing), or to transform the map coordinate system to another one.

To cover a large area with satellite data for multi-source forest inventory applications, there is usually a need to use imagery from different dates, or even from different years. Differences between images can rise from image data processing algorithms applied, and also from imaging conditions and bidirectional reflectance (see Tuominen and Pekkarinen 2004 and Tomppo et al. 2014). When multi-date images are used in image mosaicking, a technique of a relative calibration is needed for managing these effects. Temporally, satellite images are taken at certain time intervals as the satellite repeatedly passes over the region. The availability of satellite images is therefore often limited by the lack of cloud-free weather conditions and also the temporal revisit time, i.e. the temporal resolution of the system.

Tuominen and Pekkarinen (2004) developed a local correction approach and showed that digitized colour infrared aerial photographs could be successfully corrected for bidirectional reflectance in boreal forest conditions using Landsat satellite data as reference. In their study, the local correction was evaluated by using the  $k$ -NN estimation of forest attributes. They applied local coefficients based on a ratio of the mean values obtained for both the target image and the reference. Tuominen and Pekkarinen (2004) thus determined local units for which the correction coefficients were computed, as Landsat image pixels, image segments or moving circles. Tomppo et al. (2010, 2014) applied a correction approach with Landsat images and used MODIS images as a reference to match mean and variance in the image data before mosaicking the Landsat data. The different pixel sizes were accounted for by averaging, and the necessary coefficients were calculated for pixels that were cloud-free in both images.

For calibrating a set of images to a reference image, spectrally compatible image bands are required, and the time interval between images should be small for minimizing the risk of man-made changes in the landscape (Xu et al. 2012). The approach developed by Tuominen and Pekkarinen (2004) has been applied in several studies when combining remote sensing images to cover larger areas (Xu et al. 2012).

### 1.3.2 *Selecting parameters for nearest neighbour estimation*

In satellite image-based NN applications, the nearest neighbours for a target set element (a target pixel) among all the reference pixels (those pixels covering a centre point of a field plot) are sought using a distance measure in the spectral feature space (see Kilkki and Päivinen 1987; Muinonen and Tokola 1990; Tokola et al. 1996; Tomppo et al. 1998; Tokola 2000; McRoberts 2012). The Weighted Euclidean distance in the spectral space is a commonly used distance measure (Tokola and Heikkilä 1997), as is the Euclidean distance (Katila and Tomppo 2001) or regression-based distance (Tokola et al. 1996; Holmström and Fransson 2003). The weighting of different spectral variables is an obvious problem when defining the distance metric in the spectral space (Tomppo and Halme 2004).

By using  $k$ -NN, each of the neighbours (i.e., the  $k$  reference pixels) of a target pixel in turn gets a weight calculated, based on the spectral distance between the neighbour and the target pixel. Weights proportional to the inverse or inverse squared distance can be attached to the  $k$ -NNs, for instance, when conducting pixel-level predictions. The largest weight is then assigned to those neighbours being spectrally closest to the target pixel (Tokola et al. 1996; Tomppo et al. 2009a). It is also possible to apply equal weights for all  $k$  reference observations in the estimation (Haapanen and Tuominen 2008).

For NN estimation, the variables employed in the distance metric together with a value of  $k$  are selected as they are estimation parameters for the  $k$ -NN (see Tomppo et al. 2009a). Furthermore, the maximum geographical distances in horizontal and vertical directions can also be employed in indicating the set of feasible NNs when determining the  $k$ -NNs. When available, ancillary data have been utilized in the estimation, e.g. for stratification. When applying the weighted Euclidean distance, the parameters of the  $k$ -NN also include the weights of the features in the Euclidean spectral distance measure (see Tokola et al. 1996; McRoberts and Tomppo 2007). Besides spectral variables, ancillary variables (e.g. map form predictions of mean volumes by tree species describing the coarse scale variation of a forest characteristic) have been utilized in the distance metric. Field data of the current or preceding inventory would be required for this improved  $k$ -NN approach ( $ik$ -NN) that has been applied in the Finnish MSNFI (Tomppo and Halme 2004; Tomppo et al. 2009a).

The selection of the  $k$ -NN estimation parameters is performed, for example, by calculating the root mean square error (RMSE) and estimate of bias of pixel-level predictions using leave-one-out cross validation and available field sample plots. The selections are not independent (see Tomppo et al. 2009a). For selecting and weighting features for the distance metric, several algorithms – including Genetic Algorithms (GA) – have been applied to automate this task (Tomppo and Halme 2004; Haapanen and Tuominen 2008; Packalén and Maltamo 2007). Tomppo et al. (1999) have concluded that too many NNs, indicated by large values of  $k$ , reduce the natural spatial variation of the estimates, and therefore, a smoothed output is finally obtained. This feature of the  $k$ -NN technique has also been emphasized by Holmström et al. (2001).

### 1.3.3 *Estimating forest variables*

In forest variable estimation (Figure 1), the chosen estimation parameters are used in a pixel-by-pixel-based  $k$ -NN estimation. Estimates for a target area can be computed using field data drawn also from outside the target area, when a prerequisite assumption made about the

similarity of their forests holds true. For a sufficiently large area, results have been compared to the estimates and error estimates based solely on field data (Tomppo et al. 2009a, p.31).

Wall-to-wall thematic maps of forest variable predictions can be produced, as the estimation is carried out on a pixel-by-pixel basis (e.g. Tuominen et al. 2010). For categorical variables, the mode or median value can be used as a prediction, instead of a weighted average as is used for continuous variables (see Tomppo et al. 2009a; 2009b). In the  $k$ -NN prediction, the weights are positive and so they can be interpreted as area weights (see Tokola et al. 1996; Tomppo 1996), representing area proportions by each plot. Therefore, summary results for the area of interest (a set of target pixels in the area of interest) can be produced by aggregating the area weights over the region by reference plot.

For implementing the necessary calculation procedures and map presentations, there are open source tools available, such as GRASS GIS (Neteler and Mitasova 2008), the QGIS system (QGIS 2017), and the R software package (R Core Team 2017).

## 1.4 Objectives

Remote sensing materials constitute an essential source of data in estimating forest attributes. The main objective of this dissertation was to use and explore the capability of the NN-based multi-source forest inventory approach in regions representing different forest conditions. The further use of the results of a multi-source approach is examined in a case study in Finland for calculating technical bioenergy potentials. In Studies I-IV, multispectral images are used, yet the approaches are also open to materials obtained from active sensors like ALS and SAR sensors. The specific aims of the studies included in the dissertation can be itemised as follows:

- Study I: To present an approach for incorporating indicators of spatial variation into the estimation of forest parameters and compare its performance with other spectral features.
- Studies II and III: To apply and further develop methods in multi-source forest inventory tasks using different kinds of remote sensing data and forest data.
- Study IV: To utilize results from a multi-source forest inventory case study and present an approach for calculating biomass potential in a selected region.

There can be several variations in the above-presented workflow (Figure 1) depending on the sampling design and the details of the field data and ancillary data. For example, a forest cover map was constructed separately by using the  $k$ -NN estimation of a category variable in study II. Moreover, the forest category area of study III could also be extracted from the existing map of forest polygons. Study IV provides a solution to incorporate biomass estimation results from a multi-source approach for further scenario analyses including spatial constraints, and thus shows how the results of the approach may be utilized in the future.

## 2 MATERIALS

### 2.1 Study areas and field data

The study areas in studies I and IV are in Finland and represent boreal forests, whereas the study areas of studies II and III are located in Nepal and Vietnam respectively, and in the ecological zones of tropical forest (see studies I-IV and maps of FAO Global Ecological zones viewable in FAO GeoNetwork 2018).

The data in study I was collected from the area of the Helsinki University Experiment Station in Hyytiälä, in South-Western Finland. In study IV, the target area comprised the region of the Central Finland Forestry Centre.

The target area in study II was the Terai region, that is the southernmost of the five physiographic zones of Nepal. There are three separate sub-regions in Terai; in study II, Western Terai comprised the two westernmost sub-regions, and Eastern Terai consisted of the easternmost sub-region. Terrain in the Terai region is topographically less complex compared to the other physiographic zones, and the elevation varies from 60 to 330 m above sea level. In the map of ecological zones with physiographic regions in Nepal presented by Lillesø et al. (2005, p. 49), the study area in study II represents the lower tropical ecological zone. The study area featured in study III was the region of Kon Tum province in Vietnam, located in the north-western part of the central highlands region.

The field material in study I comprises a set of compartment-level forest parameters in Hyytiälä, Finland. The total size of the area was 125 ha and there were originally 73 forest compartments that were homogenous with respect to tree and soil properties. The area is mainly mineral soil. Data was collected in 1989 by the University of Helsinki, Department of Forest Resource Management. Stand-level variables were calculated from sample plot measurements drawn from a systematic grid (50 m × 25 m) of variable radius field sample plots. Stand boundaries were overlaid on the sample plot grid. Compartment-level results were then calculated from plots falling within the stand boundaries. Treewise volumes were calculated using Laasasenaho's (1982) taper curve models. Small stands (with an area less than 0.3 ha), stands dominated by deciduous species (n=3) and young sapling stands (n=3) were left out due to their rarity in the data. In the field material, there were 59 forest stands that ranged from young to mature stands, and were dominated by Norway spruce (*Picea abies* (L.) Karst.) and Scots pine (*Pinus sylvestris* L.). The stand area ranged from 0.30 ha to 11.11 ha with a mean area of 1.87 ha, and the stand age ranged between 18–107 years, with a mean age of 63 years (study I).

In study II, the field materials and visual interpretation data originated from an operative forest inventory project, i.e. the Forest Resource Assessment project of Nepal (FRA Nepal). First, a sample grid of visual interpretation data was utilized in a classification approach for producing a forest cover map. Second, field plot data was used in volume mapping and for checking classification accuracy. In the Terai region, a 4 km by 4 km grid was used to locate sample units, i.e. square clusters with a side length of 300 meters. Each cluster consisted of 6 sample plots, i.e. 3 plots 150 m apart in each of the two sides in a North-South direction. All 6 plots were used as visual interpretation plots (7533 observations). In the two-phase sampling method, the clusters were selected to a field sample by strata. In the selected cluster, the four plots at the cluster corners were then field-measured. The field plot material in Terai consisted of 217 field-measured sample plots.

In study III, the field material also consisted of existing forest inventory data from systematically located permanent plots, each having consecutively arranged subplots, with 20 subplots in a north-south direction and 20 subplots in an east-west direction. The study material for study III comprised field measurements from 133 sample plots established between January 2007 and January 2010. For satellite image-based volume mapping, the subplot material was compiled using the forest mask based on existing digital map data of land use or forest type and by selecting every second subplot to be used in field reference material, resulting in 2094 subplots.

In study IV, a wall-to-wall raster map of biomass variables obtained for the area of the Forestry Centre of Central Finland (Tuominen et al. 2010) was used as a starting point in analysing biomass potential. However, a separate analysis for the stump recovery rate constraint was carried out using existing field plot data from mature stands in southern Finland, selected from three data sets denoted as SPATI, KYMI and ENSO (see Anttila et al. 2001). Altogether 146 stands were used in analysing the stump recovery rate, including Scots pine stands, Norway spruce stands, or mixed stands of Scots pine and Norway spruce. SPATI contains a set of fixed area sample plots spanning the years 1988 – 1994 in North Karelia Finland, the materials of ENSO (1991) and KYMI (from 1984 and 1985) contain relascope sample plots originally established to check the inventory by compartments.

## 2.2 Remote sensing data

In study I, remote sensing data was comprised of a digitally orthorectified aerial photograph, whereas satellite image materials were used in studies II and III (Table 1).

The colour infrared aerial photo used in study I was taken on June 12, 1989 at a scale of 1:30 000, with a Wild RC20 camera. The digital image was produced by digitally scanning the original negative using 900 dpi resolution, and then orthorectifying the image to a 0.80 m pixel size using an elevation model from the Finnish National Land Survey.

**Table 1.** Remote sensing materials in studies I-III; (WRS = Worldwide Reference System, path/row).

Image source	Image reference	Date	Study
Aerial photo	–	1989-06-12	I
MODIS (MYD09A1)	tile h24v06	2010-02-10...2010-02-17	II
MODIS (MYD09A1)	tile h25v06	2010-02-10...2010-02-17	II
Landsat TM	144/40 (WRS-2)	2011-03-27	II
Landsat TM	143/41 (WRS-2)	2010-02-25	II
Landsat TM	142/41 (WRS-2)	2010-02-18	II
Landsat TM	141/41 (WRS-2)	2010-02-11	II
Landsat TM	140/41 (WRS-2)	2010-02-04	II
Landsat TM	140/42 (WRS-2)	2010-02-04	II
Landsat TM	139/42 (WRS-2)	2010-01-28	II
MODIS (MCD43A4)	tile h28v07	2011-02-02...2011-02-17	III
Landsat TM	124/50	2011-02-07	III
Landsat TM	125/50	2009-02-08	III
Landsat TM	125/49	2011-02-11	III

**Table 2.** MODIS spectral bands 1–7, Landsat TM bands and spatial resolutions (see Lillesand et al. 2015 p.374; USGS Landsat Missions 2017).

Sensor and band	Bandwidth	Resolution (m)
<b>MODIS</b>		
1	620–670 nm	250
2	841–876 nm	250
3	459–479 nm	500
4	545–565 nm	500
5	1230–1250 nm	500
6	1628–1652 nm	500
7	2105–2155 nm	500
<b>Landsat TM</b>		
1 Visible	0.45–0.52 $\mu\text{m}$	30
2 Visible	0.52–0.60 $\mu\text{m}$	30
3 Visible	0.63–0.69 $\mu\text{m}$	30
4 Near-Infrared	0.76–0.90 $\mu\text{m}$	30
5 Near-Infrared	1.55–1.75 $\mu\text{m}$	30
6 Thermal	10.40–12.50 $\mu\text{m}$	120
7 Mid-Infrared	2.08–2.35 $\mu\text{m}$	30

In studies II and III, MODIS data products and Landsat satellite data were used, with the former used as a reference for relative calibration, and the latter for estimating forest parameters using *k*-NN. For the gap-filling work in III, some older Landsat image data from December 2004 was also utilized. It can be noted here that some underlying analyses (such as the visual interpretation in study II, and the vector map of land use in study III) were based on high-resolution satellite materials. In study IV, the segmentation for producing stand delineation for the biomass potential analysis was based on a satellite image mosaic built from several images used in the Finnish MSNFI, from IRS-P6 and SPOT-5 satellites (Tomppo et al. 2012).

The spectral bands in the MODIS MYD09A1 data product and in Landsat TM imagery are presented in Table 2. MODIS products MYD09A1 and MCD43A4 provide 500 metre reflectance data of the MODIS “land” bands 1–7 in an 8-day or 16-day period, respectively (USGS 2018). Landsat TM band 6 was not used in the analysis, and MODIS data products with a 500 m resolution were utilized as a reference material for the relative calibration approach applied.

### 2.3 Ancillary digital data

In study I, a digital elevation model from the National Land Survey of Finland (NLS) was used to orthorectify the digital aerial photograph.

In study II, the region boundaries of Terai were compiled by the FRA Nepal project team, and visual interpretation was also aided by the topographical map layers available in Google Earth imagery (Google Earth 2018).

In study III, non-forest areas were masked out using an existing vector map of forest polygons created by the Forest Inventory and Planning Institute (FIPI) located in Hanoi, Vietnam. Also, data available from a digital elevation model (DEM); more precisely SRTM

90 m Digital Elevation Data, version 4.1 (Consortium for Spatial Information 2018), was used in image pre-processing.

In study IV, the map data contained municipality boundaries and a DEM from NLS, conservation and Natura2000 areas from the Finnish Environmental Institute, and road data and forest attribute estimation based on the Finnish MSNFI (Tomppo et al. 2012). A digital elevation model of a 25 m resolution was used in separating areas with a steep slope constraining forest operations (study IV).

### 3 METHODS

#### 3.1 Relative calibration of satellite images

In building a Landsat image mosaic, which was conducted in studies II and III, a local relative calibration was applied with a method combined from the approaches presented by Tomppo et al. (2010) and Tuominen and Pekkarinen (2004).

The correction function (see Tomppo et al. 2010) applied for a pixel  $(x, y)$  was as follows:

$$\hat{f}_i(x, y) = a_i(x, y) \times f_i(x, y) + b_i(x, y) \quad (1)$$

where  $\hat{f}_i(x, y)$  is the corrected data for the pixel  $(x, y)$  in band  $i$ ,  $f_i(x, y)$  is the uncorrected data in band  $i$ . Parameters  $a_i(x, y)$  and  $b_i(x, y)$  were computed for a pixel  $(x, y)$  as follows:

$$a_i(x, y) = sd_{M_j}(x, y) / sd_{L_i}(x, y) \quad (2)$$

$$b_i(x, y) = avg_{M_j}(x, y) - avg_{L_i}(x, y) \times a_i(x, y) \quad (3)$$

where  $i$  denotes a Landsat TM band, and  $j$  denotes a MODIS band that is compatible with  $i$ . Raster map algebra was used to compute raster maps “ $avg_{L_i}$ ”, “ $sd_{L_i}$ ”, “ $avg_{M_j}$ ” and “ $sd_{M_j}$ ”, i.e., which represent the means and standard deviation values of the Landsat TM and MODIS data in compatible spectral wavelength bands  $i$  and  $j$ , respectively. They are computed using a  $w \times w$  moving window from an image in resolution  $c$  corresponding to the reference image (MODIS). Averaging was used to change resolution of the Landsat images in creating raster maps “ $avg$ ” and “ $sd$ ”. MODIS bands 3, 4, 1, 2, 6 and 7 were used as compatible bands for Landsat TM bands 1, 2, 3, 4, 5 and 7.

In studies II and III, a value of  $c=500$  m was used. In study II,  $w=21$  was selected based on the visual appearance of the image mosaic – the means and standard deviation values were then calculated in a  $21 \times 21$  moving window (10 km  $\times$  10 km) after averaging the Landsat images to 500 metre resolution. In study III, values  $w=21$  and  $w=41$  were tested by the correlation of image band values and a forest variable, i.e. volume.

In studies II and III, the aforementioned approaches were combined as follows: the coefficients were calculated locally in a moving window, as presented in Tuominen and Pekkarinen (2004), and the coefficients for the adjustment calculated following the principles

by Tomppo et al. (2010). It can be noted that the parameters follow the form presented and derived for an image normalization procedure by Du et al. (2002, p. 126) – see also Xu et al. (2012, p 72). The tools necessary for the raster calculation and analysis were available in GRASS GIS (Neteler and Mitasova 2008).

Corrections were calculated separately for each Landsat image, after which a mosaic was created. A visual inspection was used to guide determining the range of the size of the moving window. A 500 metre resolution was selected as it was the same resolution that featured in the MODIS image data. Optionally, image DN values can be scaled to 8-bit integer values, and in studies II and III they were normalized during the next phases, i.e., feature selection and  $k$ -NN estimation, so as to account for the scale of the image data.

### 3.2 Computing spectral features

NN techniques were used in studies I, II and III. In study I, forest stand-level feature variables were computed and they were based on a digital aerial photograph resampled to a 0.80 m pixel size. Features variables included mean values in red, green and blue bands (r, g and b respectively). Also an indicator of local variability (rsd) was computed using red band, as a mean value of standard deviation in a  $13 \times 13$  moving window inside the stand. In a similar manner, a texture feature variable, angular second moment (ASM) was computed for each stand using 40 digital number (DN) classes and a  $13 \times 13$  window (Haralick et al. 1973). Empirical omnidirectional variogram curves were calculated from a sample of randomly located L-shaped clusters (0.80 m sample interval) and there were 26 clusters in each stand; thereafter 25 points from the computed variogram curve were selected as indicator variables (i.e., feature variables) at 1-metre lag intervals. The calculation of semivariances and textural feature variables was carried out according Carr and Miranda (1998; see also Anttila 2002).

In study II, the image data comprised Landsat image mosaic bands after relative calibration based on MODIS data. For the forest/non-forest classification, the spectral features included image mosaic band values corresponding to Landsat bands 1 to 5 and 7 at 30-metre resolution. For the volume mapping, the band ratios and Normalized Difference Vegetation Index (NDVI) were also included in the feature set.

In study III, the image mosaic was constructed in a similar way to that of study II, i.e., the spectral feature set in analysing volume estimation in study III consisted of image mosaic band values, band ratios and the value of NDVI. In the  $k$ -NN analysis and estimation (II, III), features were first scaled to standard deviation one.

In study III, in Kon Tum, Vietnam, there were different options in the image pre-processing phase and their parameters were evaluated in making the image mosaic. The first of these phases was selecting the neighbourhood size (10 km vs. 20 km) in the local calibration. The second option to test was a median filtering (in a  $3 \times 3$  or  $5 \times 5$  -pixel window) of the image data, and thirdly, a DEM-based radiometric correction approach was applied as presented in Tomppo et al. (2008a, p.36). Parameter values for the two first of the aforementioned optional pre-processing steps were evaluated by examining the correlation between stand volume and image bands. The power parameter value in the third option (i.e. the DEM-based correction) was analysed by examining the RMSE and bias of volume estimation when parameter values of 0.00, 0.0125, 0.0250, 0.0375, ..., 0.500 were tested in a grid search.



**Table 3.** Nearest neighbour estimation methods used in studies I-III. (CCA = Canonical correlation analysis; GA = Genetic algorithm; FS = feature selection).

Study	Forest variable	Distance	FS	Plot weights
I	Volume	MSN	CCA	Inverse distance
II	Forest/ non-forest	Euclidean	user-defined	Equal weights
	Volume	Euclidean	GA	Inverse distance
III	Volume	Euclidean	GA	Inverse distance

### 3.3 Nearest neighbour techniques in the estimation of forest variables

Nearest neighbour techniques were utilized in a manner presented in Table 3. In study I, the target and reference elements are forest stands, whereas in studies II and III they are pixels in satellite images.

In study I, the method used in stand volume estimation was based on the approach presented by Moeur and Stage (1995), i.e., Most Similar Neighbours analysis (MSN). In the MSN similarity measure,  $D^2$  (Equation 4), between a target element  $u$  and a reference element  $j$  is formulated as:

$$D_{uj}^2 = (X_u - X_j)\Gamma\Lambda^2\Gamma'(X_u - X_j)' \quad (4)$$

where  $X_u$  and  $X_j$  are feature variables of elements (observations)  $u$  and  $j$  ( $1 \times p$ ),  $\Gamma$  is a matrix of canonical coefficients of feature variables ( $p \times s$ ),  $\Lambda^2$  is a diagonal matrix of squared canonical correlations ( $s \times s$ ),  $s$  is the number of canonical correlations used, and  $p$  is the number of feature variables.

Canonical coefficients originate from canonical correlations, where the aim is in finding linear combinations  $U$  and  $V$  for target variables ( $Y$ ) and feature variables ( $X$ ), which maximize the correlation between them. In the study I,  $s$  was equal to 1, i.e. the vector of canonical coefficients related to stand volume were used. In Equation 4, the feature variables (i.e., the indicator attributes) are the image data-based variables that act as predictor variables, or independent variables, and the forest variables act as target variables (i.e., design attributes), i.e., they comprise the group of dependent variables for the similarity measure. In study I, the squared distance function to measure the similarity was based on canonical correlations between a forest variable (stand volume) and there were several sets of spectral features that were tested. The  $k$ -MSN method was applied, i.e., the set of  $k$  nearest neighbours for a target observation were searched by finding the closest  $k$  reference observations according to the similarity measure (Equation 4).

In studies II and III, the population units were the pixels in a satellite image. The satellite image bands were used as the feature variables, with observations for all of the population units. The nearest neighbours for a target pixel  $i$  among all reference pixels (the pixels covering the centre point of a sample plot) were determined using a weighted Euclidean distance in a spectral feature space (see Tokola 2000):

$$d_{ij} = \sqrt{\sum_{h=1}^{n_b} [p_h(b_{ih} - b_{jh})]^2} \quad (5)$$

where  $n_b$  is the number of bands,  $i$  is a target set element for which a prediction is sought, and  $j$  is a reference set element;  $b_{ih}$  and  $b_{jh}$  are the spectral values of the pixels  $i$  and  $j$  on band  $h$ , respectively, and  $p_h$  is the empirical weight for band  $h$ .

For the target pixel  $i$ , the  $k$ -nearest neighbours, i.e. the set of reference pixels to which the Euclidean distance in spectral feature space from the target pixel  $i$  is smallest,  $K(i) = \{j_1(i), \dots, j_k(i)\}$  were sought.

In the case of a continuous forest variable, such as volume, the weight  $w_{ij}$  for each neighbour  $j \in K(i)$  was determined to be inversely related to its distance to the target pixel  $i$ :

$$w_{ij} = d_{ij}^{-t} / \sum_{j \in K(i)} d_{ij}^{-t} \quad (6)$$

where  $t$  is a user-defined parameter ( $t \geq 0$ ). In studies II and III, a small positive number was given for zero distances and the value  $t = 2$  was used in (Equation 6). In study I, weights were determined in a similar manner, but a constant value of 1 was added to the similarity measure (i.e. to the spectral distance) to deal with zero distances, and the value of  $t=1$  was used (Equation 6).

A nearest neighbour prediction ( $\hat{y}_i$ ) for a target element  $i$  was then computed as:

$$\hat{y}_i = \sum_{j \in K(i)} w_{ij} y_j \quad (7)$$

where  $y_j$  is the observed value of the forest variable in reference element  $j \in K(i)$ .

In the case of a category variable such as the forest cover mapping in study II, the mode value of the FAO land use class among the  $k$ -nearest neighbours was the predicted class for the target pixel. The band weight ( $p_h$ ) was set to 1 for all bands.

In the distance function (Equation 5) the weights for the spectral features were sought using a heuristic method, i.e. a genetic algorithm-based approach via the ‘genalg’ package of the R statistical software package (R Core Team 2017). The genetic algorithm approach was used in two modes: on/off mode, where the aim is feature selection, and in simultaneous mode where features are selected and their weights are sought. In GA, the goal function is formulated so as to minimise the sum of RMSEs and biases of the target variables and any possible penalty, and this was applied in study III to limit the number of spectral features in the model.

Cross-validation is a step in building the  $k$ -NN model, and the accuracy of the forest variable estimate at the plot level (or at the stand level in study I) was compared with values of RMSE and estimate of bias of pixel-level predictions.

### 3.4 Cross-validation and feature selection

For the validation of the results of continuous variables, leave-one-out analyses were conducted, and common validation criteria, i.e. RMSE and bias, were calculated for the continuous variable of stand volume. The RMSEs and biases were determined as follows:

$$\text{RMSE} = \sqrt{\sum_{i=1}^n (y_i - \hat{y}_i)^2 / n} \quad (8)$$

$$\text{bias} = \sum_{i=1}^n (y_i - \hat{y}_i) / n \quad (9)$$

where  $y_i$  is the observed value,  $\hat{y}_i$  the predicted value of the given characteristic, and  $n$  is the number of observations. The relative (i.e. percent) RMSEs and biases were calculated by dividing the absolute RMSEs and biases by the means of the respective values from the observations and multiplying the resulting quotients by 100.

In study I where the  $k$ -MSN method was applied, feature sets were designed manually, and the weights for the features in the similarity measure (i.e. distance function) in the search of neighbours, were computed using the canonical correlations. The performance of the feature sets was evaluated using RMSE and bias of the volume estimates at forest stand level. Values 1, ..., 10 of the parameter  $k$  (the number of neighbours) were analysed in a similar manner. The first of the feature sets tested contained image pixel mean values in the red, green and blue bands in the forest stands, and the feature set in the model was enlarged to contain all of the spectral features (r, g, b, ASM, values of empirical semivariance).

In the forest/non-forest classification scheme carried out in study II, Landsat image mosaic band values were used in the  $k$ -NN estimation. Equal weights were manually given for the bands in a Euclidean distance function. For this case of a category variable (i.e. forest cover), classification accuracy was studied via indicators based on the confusion matrices (error matrices) and included producer's accuracy, user's accuracy, overall accuracy and Kappa statistic (KHAT) (Congalton 1991; Congalton and Green 2009; Olofsson et al. 2014; Campbell 2007). The error matrix is a simple cross-tabulation of the class labels allocated by the classification of the remotely sensed data against the reference data for the sample sites (Olofsson et al. 2014). Characterisations of KHAT-based categories as "strong agreement" (i.e. > 80%), "moderate agreement" (i.e. 40-80%) and "poor agreement" (i.e. < 40%) have been presented by Congalton and Green (2009).

The classification accuracy was accounted for in the selection of the  $k$  value, mainly by inspecting empirical distributions of the KHAT values at different  $k$  values. The Monte Carlo approach was used, where for each value of  $k \in \{1, 3, 5, \dots, 15\}$ , 5000 test samples of 1000 reference elements were randomly selected from the set of reference elements, to act as test set of target elements. The remaining elements not included in the sample comprised the reference set. The Kappa statistic value was used as a classification accuracy indicator, and KHAT was then computed for each test sample. In this way, the empirical distributions of KHAT were produced with a varying value of  $k$  to guide the selection of  $k$  value. Visual inspection plots (i.e. the 1<sup>st</sup> phase plots) were the elements used in test samples.

In constructing a forest/non-forest raster map, the post-processing included a  $3 \times 3$  mode filter (for removing the salt-and-pepper effect), reclassifying non-forest categories into a single class and excluding forest segments having an area of less than 0.5 ha. In the end, field-observed values were also used as reference data in checking the accuracy of the forest cover mapping.

In study II, the  $k$ -NN approach was applied also for volume mapping, i.e. in estimating a continuous forest variable. The feature selection and the weighting of the features (i.e., band weights  $p_h$  in Equation 5) in the Euclidean distance function were conducted using a genetic algorithm-based approach available in the statistical software package R (R Core Team

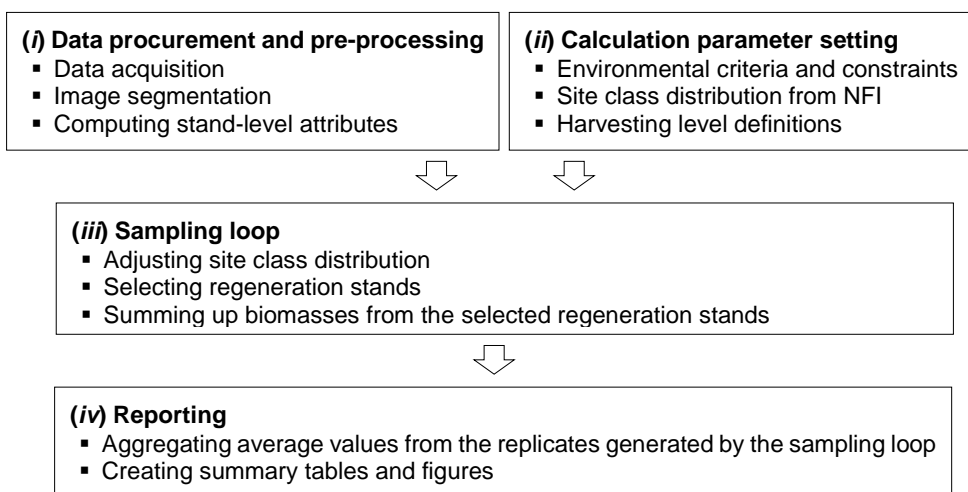
2017). For the algorithm, guiding parameters of population size, number of iterations, elitism and mutation chance were given values of 1000, 500, 40% and 0.05, respectively. The goal was to minimize the sum of RMSE and bias for the stand volume. To create a thematic wall-to-wall map for the growing stock volume, the predictions were classified in classes of 50 m<sup>3</sup>ha<sup>-1</sup>. The reference set comprised those pixels in which the centre points of field checked plots were located.

In study III, the Euclidean distance function was also used and candidate models were tested either with equal weights for the spectral features, or the weights were searched using GA. Two functions developed for continuous variables in GA were used: on/off feature selection or a simultaneous feature selection and weight search. The value of  $k$  was also searched using GA. The number of neighbours ( $k$ ) in the analysis was 1, ..., 15, and the number of variables in the model was controlled by including a penalty to the GA if there were more than 6 variables in the model. Similarly to study II, a classification of volume predictions into classes of 50 m<sup>3</sup>ha<sup>-1</sup> was applied in making the thematic map of volume.

### 3.5 Calculation procedure for the bioenergy potential of forest chips

The framework in calculating the technical potential of forest biomass presumes a stand-level forest database of forest attributes. The steps included in the calculation procedure for the bioenergy potential of forest chips in study IV are presented in Figure 2. To summarize: forest stand register over a large area was used in computing aggregations of forest biomass variables. The calculation procedure was guided by exogenously defined harvesting levels, that act as scenarios to control the intensity of the forestry operations, together with environmental criteria and constraints at stand level. Reported potentials are average values from replicates generated in a sampling loop that is introduced to account for, e.g. the variation caused by the selection of stands for regeneration. The types of forest biomass examined in study IV are primary forestry residues, i.e. logging residues and stumps.

Data procurement and pre-processing (Figure 2) includes the preliminary working steps for the necessary input forest stand attributes. Wall-to-wall raster maps of biomass variables from a multi-source forest inventory case study in the area of the Forest Centre of Central Finland (Tuominen et al. 2010) were used in combination with other forest variables originating from raster maps from the MSNFI of Central Finland (Tomppo et al. 2012). The satellite image data from SPOT-5 and IRS-P6 satellites also originated from the Finnish MSNFI (Tomppo et al. 2012). Image segmentation algorithms presented by Pekkarinen (2002) were used to delineate stand boundaries: An average filter (3 × 3 pixel window) was applied to smooth the image mosaic and the process included three iterative rounds of region merging. ArcGIS utilities (Esri 2017) were used to find the centroids of the segments. Non-forestry land was excluded based on the thematic map data of MSNFI, and nature conservation areas and Natura 2000 areas were excluded based on digital map data. Raster GIS zonal analyses were then used in calculating necessary segment-level forest attributes, i.e. mean or mode values (category variables). In this way, forest stands in the calculation system were then based on image segments furnished with the calculated forest attributes. Distance from roads and steepness of slope were also computed and added to the stand attribute table.



**Figure 2.** Working steps and issues in the calculation procedure for the bioenergy potential (study IV).

Calculation parameters (Figure 2) like those for technical and economic accessibility, together with the environmental criteria affecting the bioenergy potential of forest chips, were incorporated into the procedure following the guidelines for harvesting forest biomass for energy presented by Tapio (the Finnish Forestry Development Centre) (see Koistinen et al. 2016 for a current edition of guidelines), in addition to the general Finnish forestry guidelines (see Äijälä et al. 2014 for the current edition of the guidelines). Technical accessibility criteria (minimum recovery rate values of logging residues and stump extraction, the proportion on unmerchantable stem top, steepness of slope) and economic accessibility (minimum values of the recovery volumes for logging residues and stumps per stand, minimum stand area) were introduced as constraints in the system. The environmental protection of soil, water and remaining trees was included by implementing buffer zones, and by giving a list of feasible site fertility classes. These constraints served to define the exogenous factors to be fulfilled for a feasible technical and economic accessibility of the stands, and also to respect the principles of environmental protection. Optional constraints were given to actual forwarding distance and dominating tree species in the calculations.

The value for stump recovery rate had to be analysed in a separate calculation that was based on a set of existing field materials of forest stands (see section 2.1); One hundred simulation runs were conducted for each of the stands in the materials, following the pre-mentioned forestry guidelines (see also Kärhä 2012; for stump diameter see Repola 2008, 2009):

- all stumps with a diameter of less than 20 cm were left on the harvesting site
- in addition to the small stumps above, 25 larger stumps per hectare were not extracted and this selection is done randomly, starting from stumps of deciduous tree species.

Site class distributions were checked from the Finnish NFI (Peltola and Ihalainen 2012). Harvesting levels for the time period 2000-2009 were then examined using the annual statistics of roundwood removals at municipality-level (see Luke 2017), and the proportion of roundwood by felling method (Torvelainen 2010) was applied in estimating the share of regeneration cuttings. Three scenarios (i.e. MIN, AVG and MAX) were defined. The MIN and MAX were based on 2009 and 2007 figures, respectively.

In the sampling loop (Figure 2) of the calculation procedure, the segment-based distribution was adjusted to match with NFI-based distribution using an approach where randomly selected stands are transferred from a source class to a target class, towards the tails of the distribution. This adjustment was made because it was noted that pixel-by-pixel mode values had produced a more peaked distribution in the whole region compared to the actual distribution. The selection of the forest stands to final fellings (i.e. the source of forest chips and the origin for the bioenergy potential) were selected randomly from among the feasible stands in the region. In reporting (Figure 2), the bioenergy potentials were then calculated as averages from the replicates generated by the sampling loop using necessary unit conversions. Using the replicates, the coefficient of variation could also be computed to determine the sampling variance in the results.

The method in study IV is categorizable as a *resource-focussed assessment* and a *spatially explicit analysis* (Vis et al. 2010). The reserves of forest chips are calculated in a way utilizing the spatial explicit form of the raster maps. The delineation of forest management units was carried out using an image segmentation approach (cf. Mäkelä et al. 2011). This enabled applying regulations, a share of which depend on the size of the forest stand area, to forest operations. Sustainability issues are addressed by comparing given harvesting levels to the mean annual increment of the growing stock reported in the forest statistics.

## 4 RESULTS

### 4.1 Usability of information on variograms in image interpretation (I)

In study I, the usability of the empirical variogram curve calculated on the red band in the digitized aerial photograph was analysed by performance of image interpretation at forest stand level. The forest standwise accuracy based on cross-validation and leave-one-out analysis in the NN-based estimation of total volume was measured by RMSE and the estimate of bias. A similarity measure of quadratic form (i.e. the distance measure) was based on the approach of MSN. The explanatory variables were grouped into feature sets established for the comparisons. The number of neighbours (i.e. the value of  $k$ ) varied in a range of 1 to 10.

Lowest standwise RMSE results were obtained using those feature sets (see study I) in the distance measure that included the values of semivariance (i.e. feature sets fset\_e, fset\_g, fset\_h and fset\_f). In these cases, the relative RMSE resulted in a level of ca 18 %, that was lower than the relative RMSE-level of ca. 24–27 % acquired without the inclusion of the values of semivariance to the model (fset\_d, fset\_b, fset\_a and fset\_c). In all test cases, bias was between –0.6 % and 1.8 %.

Values of  $k$  greater than 3 offered little improvement, i.e. the RMSE level was quite stable with values  $k$  larger than 3. The bias was unstable when fewer than 8 neighbours were used.

Large values of  $k$  resulted in underestimates. Based on the residual plot in case fset\_e ( $k=3$ ), stand area had no clear effect on the performance of the volume estimation.

#### 4.2 Mapping forest cover and volume in tropical forests using $k$ -NN (II and III)

Covering the Terai region with Landsat TM satellite data utilized in study II required several Landsat images that were taken on different dates. For this reason, an approach for a relative calibration was necessary, in order to enable the combined usage of Landsat image data, field plot data, and visual interpretation plot data. The overall appearance of the image mosaic was inspected to find suitable window sizes for the calibration approach. Finally, a window of  $21 \times 21$  pixels of a 500 m -resolution was used in calculating the means and standard deviation values used for the calibration. MODIS data acted as reference material in a local calibration that was made separately for eastern and western parts of Terai. The forest cover mapping was based on an FAO land use classification made for a sample grid of visual interpretation plots. The  $k$ -NN approach was applied for mapping forest cover and volume.

The MODIS data performed well as reference data for the calibration approach. For the category variable (i.e. forest cover), the value of  $k$  was selected using randomly selected test samples. Kappa statistics (KHAT) for different values of  $k$  showed that in forest cover mapping, using values of  $k$  greater than 5 does not improve the quality of the estimation result. Kappa statistics showed 0.84 and 0.87 for  $k=5$  in Western and Eastern Terai, respectively. A value of  $k=5$  was used in the forest cover mapping, together with equal weights in a Euclidean distance calculated with image mosaic bands.

Accuracy measures were calculated using the field-observed values, 140 and 77 plots in western and eastern parts, respectively. The accuracy of the delineation of forest cover by visual interpretation was very good in both parts of Terai, with a Kappa value of ca 0.82 (i.e. strong agreement) based on the field-checked value. In Eastern Terai, the forest cover classification appeared to have the same accuracy level as the visual interpretation – the Kappa value was 0.825. In Western Terai, the forest cover map had a slightly lower Kappa value of 0.745 (moderate agreement); the user's accuracy in the "Non-forest" class was 71 %. Based only on the field plot points, the forest cover map and the visual interpretation showed a better agreement in Eastern Terai (KHAT=0.825, i.e. strong agreement) than in Western Terai (KHAT=0.65, i.e. moderate agreement).

In study II, thematic mapping of stand volume was carried out with  $k$ -NN techniques using a weighted Euclidean distance. The explanatory variables (spectral features) included  $b_1$ ,  $b_2$ ,  $b_4/b_3$  and  $b_5/b_3$ , where  $b_i$  refers to image mosaic band comparable to the  $i^{\text{th}}$  TM band. The largest weights by search conducted with a GA-based approach in the distance were given to  $b_2$  and  $b_1$ . Plotwise RMSE and bias resulted in 85.4 m<sup>3</sup>/ha (ca. 62%) and -0.541 m<sup>3</sup>/ha (slight overestimation), and  $k=4$  was used in the volume mapping. A boxplot of residuals indicated the median of residuals being close to zero in all volume prediction categories. However, some averaging effect could be noted in the volume predictions. For the thematic map of volume, reclassification into categories of 50 m<sup>3</sup>/ha were used. The target pixel data for the classification comprised of pixels belonging to the category of forest in the forest cover map and the reference data comprised the pixels covered by a field plot.

Kon Tum province was the target area of study III, and is located in the north-western part of the central highlands region of Vietnam. The aim of study III was to compile and demonstrate the use of a multi-source forest inventory -oriented processing chain to produce forest volume maps for the region. This study raised the challenges of species-rich tropical

forest structure to forest data analysis. It can be noted that a vector map of forest polygons was utilized in aggregating the subplots into forest stands for a tree height generalisation model – this subject is not covered in the main scope in this thesis, more details of the procedure of applying the NMLE modelling approach are featured in the listed publication of study III.

The relative calibration of Landsat TM images was performed using a similar approach than that which was used in study II. A  $41 \times 41$  pixel moving window and a 500 m resolution were used in computing the mean and standard deviation values as a larger window was preferred. Also, a  $5 \times 5$  median filter was applied, based on the correlation between stand volume and satellite variables. The next step was to find out if DEM-based pre-processing could improve the estimation. After a grid search ( $k=15$ , equal weights of image mosaic band values) and examining the plot-level RMSE and bias of volume estimation (i.e.  $129.2 \text{ m}^3/\text{ha}$  and  $0.11 \text{ m}^3/\text{ha}$  respectively), the power parameter was given a value of 0.250 for the DEM-based correction.

The next phase was a genetic algorithm-based search of the spectral features (feature selection), together with a search of feature weights, i.e. the coefficients of the variables in the weighted Euclidean distance function for the volume estimation. After several test runs, in the two modes of the GA procedure – on/off and simultaneous modes – it was noted that the differences in the RMSE of stand volume between the models of the test runs conducted were small. The plot-level values of RMSE and bias in the leave-one-out cross validation resulted in  $126.2 \text{ m}^3/\text{ha}$  (76.6%) and  $-0.04 \text{ m}^3/\text{ha}$  (0.03%), respectively, and the number of neighbours was 13. For the thematic map of volume, the volume predictions were reclassified into  $50 \text{ m}^3/\text{ha}$  categories and overlaid on the land use map data, i.e. the vector map of forest polygons.

### 4.3 Estimating the bioenergy potential of forest chips (IV)

Calculation of the bioenergy potential of forest chips was based on a spatially explicit method, where a stand register furnished with necessary forest attributes is presumed. Wall-to-wall raster maps of forest attributes from a multi-source forest inventory approach together with a stand delineation derived using image segmentation were used to build a stand register for study IV. By overlaying these two raster maps in a raster GIS framework, stand-level forest attributes could be computed. In the preliminary separate analysis, stump recovery rate was found to have a value of 0.9. Constraints for set-aside areas (such as nature conservation areas) were also implemented. It was noticed that the variance due to site class adjustment was very small compared to the variance due to stand selection for regeneration. To keep the variation of sample mean small enough in the results, the number of replicates in the sampling was set to a value of 500 replicates, comprising 5 site class adjustments and 100 random selections in each of them. The variations within the municipalities caused by the random selection of stands for regeneration increased with more constraints.

Regulations and criteria for technical and economic accessibility of the biomass from logging residues and stumps, together with environmental criteria, affect the availability of forest biomass, so they were implemented in the calculation model as basic and optional constraints. Optional constraints for a 300-meter maximum actual forwarding distance and another for selecting only spruce dominated stands for stump extraction were applied.

When only the basic constraints were applied, the annual forest-centre-level potential for the residues in the AVG scenario was 320 000 tonnes ( $710\,000 \text{ m}^3$ ), and this was 63% of the



theoretical potential in that scenario. After introducing an actual forwarding distance limit of 300 m, the potential for residues decreased to a relative value of 36% of the theoretical potential.

For stumps, the basic constraints in the AVG scenario resulted in a potential of 212 000 tonnes (470 000 m<sup>3</sup>) that was 38% of the theoretic potential in that scenario. An actual forwarding distance limit of 300 m and a limit for regeneration to stands dominated by Norway spruce resulted in relative values of 22% and 15% of the theoretic potential. With only basic constraints, the harvesting level MIN and MAX resulted in relative values of 25% and 43% of the theoretic potential, respectively.

Assuming the AVG harvesting level and applying all basic and optional constraints, the annual technical potential of forest chips from final fellings in Central Finland for energy is 0.26 million tonnes (dry mass), that is 4.6 million GJ (1.3 TWh). From this value, logging residues comprise a share of 70%, and stumps 30%.

## 5 DISCUSSION

### 5.1 Variograms and image texture

The utilization of image-based spatial features in study I was introduced via features (indicator attributes in *k*-MSN) derived from a variogram curve. In study I, the aim was to evaluate the usability of empirical semivariance values as features and to try to catch the effect of forest structure on the spatial variation in the image observed. The results showed that incorporating features indicating image spatial structure decreased the RMSE level of volume in the *k*-MSN estimation approach.

Anttila (2002) stated that the shape of the image segment representing a forest stand can also delimit the usability of the approach applied in study I. In a comprehensive analysis of a nonparametric estimation (i.e. the *k*-MSN approach) of stand volume from aerial photographs, Anttila (2002) noted that the smallest and elongated stands should be left out of the estimation to avoid difficulties that would otherwise be induced into the calculation of the semivariance. Exclusion of stands with a low ratio of stand area to perimeter improved the accuracy of the estimation. Using old inventory data as indicator attributes in *k*-MSN proved successful in stand volume estimation. Anttila (2002) also stated that the location of a stand in an image affects the texture of the stand, and estimation with single photographs instead of with all three was more accurate in two out of three cases. With image pixel mean values and semivariance features only, the RMSE for volume in study I was quite small, ca. 18%, whereas Anttila (2002) reported RMSE value 37% (with features of a ratio image and semivariance) and RMSE value 44 % using only semivariance-based feature variables. However, in the case of single photographs and by taking the shape of stands into account in selecting reference stands (ratio of stand area to perimeter was used in the selection), Anttila (2002) reported comparable RMSE levels to study I for volume, when old inventory data, semivariance and ratio image variables were used as feature variables. Results in study I and the outcomes noted by Anttila (2002) partly outline the issues related to calibration methods, bidirectional reflectance in aerial photographs, and selecting reference data in applications based on the NN estimation.

Treitz (2001) has remarked that the spatial structure of a remote sensing image is determined by the relationship between the size of the objects in the scene and the spatial resolution of the sensor. A variogram is used to describe spatial variability (i.e. semivariance) as a function of lag distance. The variogram demonstrates a peak in variance (i.e. sill) when pixels become independent of one another. The lag interval to the peak in variance is known as the 'range' of the variogram (see e.g. Treitz 2001). St-Onge and Cavayas (1995) gave more attention to the range than to the sill, when they related variogram parameters and forest structure values. The sill represents the general variance in the image and can be affected by image noise or atmospheric conditions. The range of the variogram, however, is directly related to the absolute size of the objects on the ground and is measured in the same units as these objects. Tesfamichael et al. (2009) tested variogram range values calculated from a LiDAR data-based canopy height model in defining a window size for local maxima filtering. The variogram range generally proved to be a useful indicator of individual tree canopy size. Variogram analysis yielded range values that varied distinctly with spatial resolution and point density. They also mentioned the existence of periodic deviations in variograms.

Treitz (2001) analysed the relationship between variograms and vegetation types, and noted that in visible and near infrared wavelength bands of high-resolution Compact Airborne Spectrographic Imager (CASI) data, the range estimates for specific forest ecosystems varied as a function of altitude (i.e. the spatial resolution was affected by the flying altitude). At lower altitudes (e.g., 600 m) the range estimates may be linked directly to the canopy diameter of a single tree, whereas at higher altitudes (e.g., 1150 m) they may be linked to a spatial aggregation of two or more crowns coupled with their associated understory. Thus, the range parameters of variograms could represent multiple scales of information appearing in the image data, caused by the spacing of tree crowns and understory. Treitz (2001) also noted that range estimates vary as a function of wavelength, so that the ranges for the near-infrared data are greater than those for the visible data. Further, the range values for visible and near-infrared data also increased with stand complexity. It was noted that a lower semivariance is characteristic of coarser spatial resolution remote sensing data, and that complex forest ecosystems have greater magnitudes of semivariance than simpler ecosystems.

The assumption in study I was that by incorporating experimental semivariance values from a red band into a similarity measure in the  $k$ -MSN estimation of stand volume, the neighbours selected to a target stand would have a similar spatial structure appearing in the image, and that in this way, the variogram curve could be used to indicate this structure. The above-mentioned results obtained by Treitz (2001) give some support to the assumptions made in study I. Chen and Gong (2004) concluded that window size plays important role if the range parameter in a variogram model is used in the texture-based image classification of land cover. In study I, the experimental variograms were computed at stand level to cover an area large-enough for computing the features derived from a variogram curve.

St-Onge and Cavayas (1997) expressed the underlying fact that as the spatial resolution becomes higher, the pixel will no longer represent the averaged signal reflected by a number of trees, as is the case for Landsat TM images. Therefore, they concluded that poor results would be expected in classical pixel-by-pixel classification, and instead, stand mapping will have to rely on processing algorithms that analyse groups of contiguous pixels. They built an image segmentation approach, where directional variogram model-based features were used to reveal forest characteristics such as crown diameter, stand density and crown closure. They noted that there is an issue related to the linkage between moving window size and variogram measures: for stands with a uniform texture composed of small primitives, better results could be achieved with a certain level of repetition of the texture primitive assured within a single

unit of measure of the variogram. It is thus evident that due to reasons presented by St-Onge and Cavayas (1997), that the size of the moving window or the area in the forest stand in which a variogram is calculated, and also the spatial pattern of trees which make canopy layers visible in the image, contribute to the resulting variogram. Because of these aspects, the experiment in study I was carried out at stand level, aiming to obtain a variogram, well representing the target stand and its texture in the image (i.e. the results of 26 L-shaped clusters were pooled in a stand for calculating the variogram). The question of a mapping unit has been tackled in the field of forestry applications by further developing image segmentation algorithms (e.g. Pekkarinen 2002), and by an area-based method in ALS data - derived applications. For analysing texture, approaches based on a Fourier analysis are also available, as discussed by Ploton et al. (2017) in the field of tropical forest biomass assessments.

The fine-tuning of  $k$ -MSN models should be done very carefully to prevent the loss of model applicability, as suggested by Maltamo et al. (2009). They applied the  $k$ -MSN approach in estimating diameter distributions at plot-level by using ALS data gathered from Norway, and compared accuracy indicators (RMSE and bias) based on estimation data (cross-validation) and independent validation data. The estimated models should be kept less detailed with respect to the total number of their independent variables since cross-validation always tends to give overly optimistic results, and validation with independent data will often show considerably poorer reliability figures. The disadvantage of the approach applied in study I was that the number of semivariance values imported into the model was relatively high (a total of 25 explanatory variables were introduced to the model at the same time). The resulting model is regarded as data-specific and its predictions cannot be generalized. Thus, there is a potential risk of model overfitting (as discussed by Maltamo et al. 2009). The variogram could have been parametrized with a lower number of model parameters (e.g. range and sill), that could have been incorporated thereafter in the distance function (see e.g. Peuhkurinen et al. 2008b). Another approach to decrease the number of explanatory variables (instead of using empirical values as in study I) would be to adapt the approach based on Minkowski distances (see Peuhkurinen et al. 2008a). However, the Minkowski distance tells us only the magnitude of the difference between two distributions, and not where the difference is (Peuhkurinen et al. 2008a). It is also worth considering that the study material in study I was of a limited size (i.e. a single aerial photo and 59 forest stands), and that the level of the resulted accuracy was calculated by cross-validation. The  $k$ -MSN would be made more general and wider by including several forest variables as design attributes (only one forest variable, i.e. total volume, was used in study I).

## 5.2 Satellite images in forest cover and volume mapping

Having a resolution of 500 m, MODIS data was used as a reference material in a local correction that was implemented combining the method by Tuominen and Pekkarinen (2004) and the approach by Tomppo et al. (2010). The aim was to formulate a procedure where different spatial resolutions in the reference images and target images would be accounted for, along with locally scaled means and variances in the respective spectral bands. In the report by Tomppo et al. (2010), an approach was presented for adjusting bandwise means and variances, using MODIS data as a reference due to its sophisticated radiometric properties. MODIS also has a large coverage, making it well suited as a reference material. The coefficients for the correction (Equations 1–3) were computed in a moving window and

were based on a coarse resolution after averaging. The resulting correction is local, i.e. the means and variances at the coarse resolution are adjusted locally with the reference material. As in the method by Tuominen and Pekkarinen (2004), the original resolution of the target image is to be maintained. Parameters to be selected include the window size and the resolution, although it is also possible to select a coarser resolution value than the one featured in the original reference data. In studies II and III, a 500 m resolution was used, whereas the window sizes were 10 km or 20 km. These user-defined values were assumed to work well for the approach. Moreover, a sensitivity to disturbances in the reference data is affected by the window size of this local correction approach. In study II, the time interval of the MODIS image materials was close to the dates of the Landsat images. However, in the case of some of the image materials available for parts of the region analysed in study III, there were time lags of up to 2 years. The image calibration approach applied was evaluated only using the visual appearance of the result. In studies II and III, image data were normalized based on observed image values at the locations of the sample plots for setting the scale of the output image in the estimation phase, which is a required step to take for conducting NN analyses. Alternative approaches to image mosaicking would be to carry out separate NN estimation cycles for each Landsat image and then build a thematic map of volume as a mosaic. This approach would avoid the risk of having bad reference image data in relative calibration. But in that case the forest data would be utilized only inside each of those sub-regions (image areas) and could possibly become locally limited if there were small-sized sub-regions. There would rise questions such as how representative forest data there would be available for each sub-region, and an approach for a seamless volume map in the sub-region borders would be needed.

In the local correction, the means and standard deviations for the adjustment in each band are calculated in averaged Landsat image data and MODIS image data, locally in a moving window. In studies II and III, it should be noted that the aim was not in change detection. Changes in vegetation or landscape in a time window between target and reference image dates will factually hamper the image correction due to the local correction approach. It is therefore recommended that in the case of multi-temporal images and change detection, that point invariant features (PIFs) and the procedure initially suggested by Du et al. (2002) and later reviewed by Xu et al. (2012) be used in adjusting the parameters  $a_i$  and  $b_i$  in Equation 1, instead of using the local correction approach. Also emphasizing the importance of methodological tools for the use of multitemporal satellite image mosaic in a REDD+ programme, for instance, a variance-preserving mosaic algorithm has been presented by Eivazi et al. (2015), who base their approach on analysing the overlapped regions of neighbouring images.

The visual interpretation of the FAO's land use classes for the first-phase plots over the Terai region was an example of using remotely sensed data in lieu of more expensive ground observations and measurements, and well demonstrates the support obtained from remote sensing technology for forest inventory (see McRoberts and Tomppo 2007). Interpreting the land use class from high-resolution imagery enabled the forest cover classification, where the field-observed data of study II was used in validating the classification results. The development of image viewers such as Google Earth (a virtual globe and satellite imagery viewer; Google Earth 2018), greatly facilitated the use of the image data that is offered in that platform. DFRS (2015) stated that in the visual interpretation of land cover, changes in land cover between the image acquisition and interpretation, local geometrical distortions and human errors in classifying land cover can affect the quality of results. The interpreter can benefit from a direct knowledge of the context. Moreover, the spatial heterogeneity of

forest stands, the fuzziness of their boundaries, and the possible defoliation of some deciduous trees during the time of image acquisition were also recognized as factors posing challenges in the remote-sensing-based mapping of the forest vegetation and its types in Nepal (DFRS 2015).

Kappa has been criticized for its dependence on marginal distributions (Stehman 1997). The Kappa distribution computed in a data driven approach on test samples was primarily used to guide the selection of the value of  $k$ . Other accuracy measures were also calculated in the comparison (study II), and the value of  $k$  was then set at 5. A small value of  $k$  was preferred and the Monte Carlo technique compounded by the other accuracy measures served well as criteria in this selection. An independent reference sample was not available for final testing, and the accuracy measures were computed based on the field-checked plots (cf. Olofsson et al. 2014). However, in validation, the neighbour selection could have been restricted to different clusters of sample plots other than the cluster represented by the target point itself, or a condition for a minimum geographic distance could have been used to guarantee that the geographically closest plots are not selected in the evaluation (Haapanen et al. 2004). This aspect should be taken into account when validation measures of the corresponding mapping applications are conducted in the future.

Diagnostic tools such as those developed by McRoberts (2009) and McRoberts et al. (2015) can offer guidelines towards approaches for detecting outliers or influential observations. There can be field plots with combinations of characteristics measured that can substantially increase estimation errors in the cross-validation phase. In study II, however, the plot of residuals for the volume prediction classes showed that the median of residuals was near to a zero level in all of the prediction categories. For applying this kind of approach in the future, more development work towards using automated tools reviewing the data is required.

The volume mapping for the Terai region in Nepal represented a baseline application of the  $k$ -NN for a continuous variable. The genetic algorithm-based approach proved a suitable method for the selection of variables and their weights in the distance function. In study II, the largest weights were set to spectral variables representing visible green and blue bands. Two further variables represented a simple ratio of the near infrared band to the red band (a common band ratio in studies of vegetation), or a ratio of the short wave infrared band to the red band. In study III, the largest weights were given to ratios of the green band to the red band, and also to a common simple ratio, i.e. the ratio of the near infrared band to the red band. Based on volume estimation test runs that were conducted using data from the tropical forests analysed in studies II and III, it seemed that after a certain level of accuracy has been reached, the further improvements achievable by  $k$ -NN model optimization were somewhat minimal. The relative RMSE at pixel-level obtained in studies II and III showed quite large values of 62 % and 77%, respectively. This level of accuracy reflects the potential of using optical satellite data in the  $k$ -NN estimation of forest attributes in these conditions. Similarly, a DEM-based correction brought only a minor improvement. Accounting for the notes on the nature of data (Häme et al. 2013a, p.3), the DEM-based pre-processing step could have been excluded from study III. In study III, the  $k$ -NN setup applied was a result from three test runs with the GA, where 6 variables were searched to the model. The simultaneous mode in the GA implementation for the feature selection and weights search appeared to be a usable approach for finding a suitable  $k$ -NN estimation model. It is evident that there are several ways to perform a successful feature selection (see Haapanen 2014, p.29). The applied GA approach in performing the feature selection, setting up feature weights in the distance measure and searching for the value for  $k$  showed the level of  $k$ -NN accuracy that could be

reached in study III. Hence, the genetic algorithm-based automated approach for selecting these  $k$ -NN estimation parameters could reveal the potential of medium resolution satellite data available for assessing tropical forests.

One may assume that the technical development in sensors and computing capacity will go further towards having higher resolution satellite materials available over larger areas for the remote sensing of natural resources. Furthermore, the development of methodologies for inventories (also in larger areas and partly guided by REDD+ thinking) will continue to head towards approaches combining multiple sources of remote sensing data, including ALS and also high-resolution satellite remote sensing data (see e.g. Nilsson et al. 2017; Kangas et al. 2018).

As mentioned earlier, forest inventory aims to provide improved decision support for policy makers and forest owners via feeding input data into a planning system. In the planning context, forecasting future forest development with relevant growth models, calculations for the carbon balance or amounts of biomass are relevant issues in forest inventory dependent information contexts. The planning level (strategic, tactical or operative) and the size of the area of interest can set specific requirements for the quality and form of data. Naturally, the complexity of analysis rises when operating in developing countries, areas with difficult and weak infrastructure, or in species-rich tropical forests, for example. The scope in developing forest information systems starts from finding out the current state of the forest, i.e. developing methods or models for calculating stand and tree variables, and for making maps of forest resources. The monitoring and change detection aspects of remote sensing can follow, provided that the inventory and calculation systems allow these kinds of analyses, and an increasing demand is given to these two aims in developing countries by REDD+.

### 5.3 Satellite images and analysing the bioenergy potential of forest chips

Raster maps of biomass assortments produced by NN techniques (Tuominen et al. 2010) comprised the input material for the further calculations of the bioenergy potential performed in study IV. The existence of spatially continuous forest inventory data and the allometric models for different biomass assortments are prerequisites for the approach applied. This approach represents a category of spatially explicit methods (Vis et al. 2010). Satellite remote sensing was a key issue in acquiring this kind of input for biomass variables in a raster map form. For a  $k$ -NN estimation, a representative field sample was needed (Tuominen et al. 2010), and the Finnish NFI proved its importance in this role – study IV was an example of a GIS-based analysis in a planning system aimed to offer information of technical potential for forest bioenergy.

The technical biomass potentials of forest chips (i.e. assortments of logging residues and stumps) in Finland have been made available, furnished with raster maps in an open map service that is available to the public (Biomassa-atlas 2017). The procedure applied in Biomassa-atlas (2017) has been reported by Anttila et al. (2014). Based on NFI field data and MELA scenario modelling with an annual regeneration area at the level of the period 2008–2012, the potential of forest chips in Central Finland showed a value of 644 000 m<sup>3</sup>/a for logging residues (Biomassa-atlas 2017). In study IV, the annual technical potential in an AVG scenario and with basic constraints for logging residues resulted in a slightly larger value of 710 000 m<sup>3</sup>. For stumps, however, study IV resulted in a lower annual technical potential estimate (470 000 m<sup>3</sup>) than the value reported in the Biomassa-atlas (703 000 m<sup>3</sup>/a). The parameter values reported in study IV were, however, quite comparable (see Anttila et

al. 2014), and the deviance may originate partly from the approach of applying the basic constraints by image segments representing the forest stands in study IV. Constraints that are dependent on the size of a forest stand demand a comparable stand area distribution with operational forestry. In the future, special attention should therefore be paid to the image segmentation phase of input data processing when applying this spatially explicit approach.

The aim of having forest inventory data that continuously covers a large area advocates the use of a multi-source forest inventory approach in Finland, especially since the map form estimates from MSNFI-2009 were made publicly available in November 2012. Biomass estimates are also included in the raster maps available in the MSNFI (Mäkisara et al. 2016). Technically, the calculations made in study IV could be based on these biomass raster maps, and also used as data sources. One may assume that for approaches like the one applied in study IV, it would be best to use the same image data in the estimation of the raster map form data (i.e. forest variables and biomass variables) and in the image segmentation phase. Furthermore, the raster cell grids should match each other. In study IV, there were differences in these parameters and this could to some extent lower the quality of input data generation. Also, it is known that using medium-resolution satellite data, the RMSE in the pixel-level predictions of biomass or volume in the input data are large, making the use of satellite data problematic and not accurate enough in the sense of operational forest planning (e.g. Mäkelä et al. 2011, p. 1346).

MELA scenario modelling that is built on NFI data and offers a strategic planning perspective is a sophisticated tool for analysing bioenergy potentials in Finland, and these could also be calculated with less computational effort from the MELA summary reports of biomass assortments (see Anttila et al. 2014; Biomassa-atlas 2017). The possibilities to use NFI plot -level area weights from  $k$ -NN together with a stand delineation based on image segmentation for generating initial forest data of the MELA system, and also the performance of resulting scenario analyses have been a topic of recent research in Finland (see Mäkelä et al. 2011). If successful, this kind of methodology would further improve the usability of the MELA system, directly in the analysis of bioenergy potentials. Using  $k$ -NN weights in generating forest stand input data would preserve the natural structure in forest data, and may be well suited for input data generation for applications where guidelines based on forest attributes are to be applied in the selection of stands for a forestry operation or treatment, such as collecting logging residues or stumps. The use of high-resolution imagery and ALS data in this framework is worth further consideration in the future.

Defining scenarios for the minimum, average and maximum levels of harvesting was undertaken to investigate the fluctuations in the resulting potentials. The statistical input data needed for the procedure can sometimes form a bottleneck, because, for instance, the municipality-level statistics of removals are not made publicly available in Finland. The spatially explicit approach in study IV was strongly guided by the given harvesting levels, however, another option (see Anttila et al. 2014) could be to utilize large area statistics obtained by regions, and to quantify the removals in respect of areas of mature stands by municipality.

## 6 CONCLUSIONS

In the experimental case study (I), the accuracy of volume estimation was improved when empirical values of semivariance were included in the set of feature variables in a  $k$ -MSN analysis. Generally, high-resolution satellite images can prove more feasible input materials than digital aerial photographs, due to factors arising from illumination and view geometry. Attention should be paid to image data normalization and spatial resolution, as they have an impact on the range of values of semivariance and on the shape of the variogram curve. Further research would be needed on the use of variogram model parameters based on imagery of multiple resolutions, as texture indicators in the estimation of forest attributes.

The results in studies II and III corresponded with the results of earlier studies implemented using data from tropical forests in a sense that as the vegetation canopy closes, the accuracy of the estimation of forest parameters such as volume or biomass, with medium-resolution optical satellite data reaches a form of saturation level. Optical satellite image data with medium resolution can offer large area coverage, and so the applications of land cover classification and mapping can be used as components in a larger calculation system for biomass estimation and monitoring. When there are conditions with low field accessibility, then high-resolution satellite image data can serve as a basis for image interpretation, instead of carrying out more expensive ground observations. Image data in multiple resolutions and with a large coverage are important features highlighted in this work. Therefore, calculation systems that integrate multiple remote sensing data sources such as active sensor and satellite data at multiple resolutions, and multiphase field sample data, should receive the most attention in relation to tropical forests and the REDD+ process. In this context, the importance of the basic components of a forest inventory system, i.e. a representative field sample and the necessary models for tree and forest variables, cannot be overemphasised.

The GIS-driven analyses based on large area resource data from a multi-source forest inventory was technically well suited for examining the bioenergy potential of forest chips from clear cuttings (IV). In Finland it could also be technically possible to utilize results from the Multi-source NFI, where results in the forms of raster maps of biomass or forest variables could form input data for the spatially explicit calculations presented in this thesis. From the MSNFI, a municipality-level summary of the areas of mature forest, could, at least to some extent be utilized in estimating the level of harvesting removals. As remote sensing technologies are being further developed, the usability of satellite image data with higher resolutions will offer better segmentation. As estimating forest attributes comes down to a matter of accuracy, it is also evident that the development of ALS-based inventory routines can also provide a suitable source of data for calculations of the bioenergy potential of forest chips.



## REFERENCES

- Äijälä O., Koistinen A., Sved J., Vanhatalo K., Väisänen P. (eds.). (2014). Metsänhoidon suositukset. [Silvicultural guidelines]. Forestry Development Centre Tapio. 180 p. [In Finnish]. <http://www.metsanhoitosuositukset.fi/suositukset/metsanhoidon-suositukset/>. [Cited 19 Dec 2017].
- Anttila P. (2002). Nonparametric estimation of stand volume using spectral and spatial features of aerial photographs and old inventory data. *Canadian Journal of Forest Research* 32(10): 1849–1857.  
<https://doi.org/10.1139/x02-108>
- Anttila P., Haara A., Maltamo M., Miina J., Päivinen R. (2001). Metsän mittauksen tutkimusaineistoja. [Research data for forest mensuration]. Joensuun yliopisto, metsätieteellinen tiedekunta. 9 p. + CD-rom. ISBN 952-458-004-7. [In Finnish].
- Anttila P., Nivala M., Laitila J., Flyktman M., Salminen O., Nivala J. (2014). Metsähakkeen alueellinen korjuupotentiaali ja käyttö vuonna 2020. Metlan työraportteja / Working Papers of the Finnish Forest Research Institute 313. 55 p. [In Finnish]. <https://www.metla.fi/julkaisut/workingpapers/2014/mwp313.htm>. [Cited 14 Dec 2017].
- Asner G. P. (2009). Tropical forest carbon assessment: integrating satellite and airborne mapping approaches. *Environmental Research Letters* 4(3): 034009. 11 pp.  
<https://doi.org/10.1088/1748-9326/4/3/034009>
- Batidzirai B., Smeets E.M.W., Faaij A.P.C. (2012). Harmonising bioenergy resource potentials—Methodological lessons from review of state of the art bioenergy potential assessments. *Renewable and Sustainable Energy Reviews* 16: 6598–6630.  
<https://doi.org/10.1016/j.rser.2012.09.002>
- Biomassa-atlas. (2017). Biomass atlas makes Finnish biomass maps freely available to everyone. <https://www.luke.fi/biomassa-atlas/en/>. [Cited 14 Dec 2017].
- Bååth H., Gällerspång A., Hallsby G., Lundström A., Löfgren P., Nilsson M., Ståhl G. (2002). Remote sensing, field survey, and long-term forecasting: an efficient combination for local assessments of forest fuels. *Biomass and Bioenergy* 22(3): 145–157.  
[https://doi.org/10.1016/S0961-9534\(01\)00065-4](https://doi.org/10.1016/S0961-9534(01)00065-4)
- Campbell J. B. (2007). *Introduction to remote sensing*. 4th ed. New York. The Guilford Press. 626 p.
- Carr J. P., de Miranda F. P. (1998). The Semivariogram in Comparison to the Co-Occurrence Matrix for Classification of Image Texture. *IEEE Transactions on Geoscience and Remote sensing* 36(6): 1945–1952.  
<https://doi.org/10.1109/36.729366>

Chen Q., Gong P. 2004. Automatic Variogram Parameter Extraction for Textural Classification of the Panchromatic IKONOS Imagery. *IEEE Transactions on Geoscience and Remote Sensing* 42(5): 1106–1115.

<https://doi.org/10.1109/TGRS.2004.825591>

Congalton R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment* 37(1): 35–46.

[https://doi.org/10.1016/0034-4257\(91\)90048-B](https://doi.org/10.1016/0034-4257(91)90048-B)

Congalton R. G., Green K. (2009). *Assessing the accuracy of remotely sensed data: principles and practices*. 2nd ed. Boca Raton. CRC Press/Taylor & Francis Group. 183 p.

Consortium for Spatial Information. (2018). SRTM 90m Digital Elevation Database v4.1. <http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1>. [Cited 7 Feb 2018].

DFRS. (2015). *State of Nepal's Forests. Forest Resource Assessment (FRA) Nepal*, Department of Forest Research and Survey (DFRS). Kathmandu, Nepal. Publication No. 5. [http://www.dfrs.gov.np/downloadfile/state%20of%20forest\\_1470140234.pdf](http://www.dfrs.gov.np/downloadfile/state%20of%20forest_1470140234.pdf). [Cited 2 Mar 2018].

Drake J. B., Knox R. G., Dubayah R. O., Clark D. B., Condit R., Blair J. B., Hofton M. (2003). Above-ground biomass estimation in closed canopy Neotropical forests using Lidar remote sensing: factors affecting the generality of relationships. *Global Ecology and Biogeography*, 12: 147–159.

<https://doi.org/10.1046/j.1466-822X.2003.00010.x>

Du Y., Teillet P.M., Cihlar J. (2002). Radiometric normalization of multitemporal high-resolution satellite images with quality control for land cover change detection. *Remote Sensing of Environment* 82 (1): 123–134.

[https://doi.org/10.1016/S0034-4257\(02\)00029-9](https://doi.org/10.1016/S0034-4257(02)00029-9)

Eivazi A., Kolesnikov A., Junttila V., Kauranne T. (2015). Variance-preserving mosaicing of multiple satellite images for forest parameter estimation: Radiometric normalization. *ISPRS Journal of Photogrammetry and Remote Sensing* 105: 120–127.

<https://doi.org/10.1016/j.isprsjprs.2015.03.007>

Esri. (2017). Esri Products. <https://www.esri.com/products>. [Cited 28 Nov 2017].

Faaij A. P. C. (2006). Bio-energy in Europe: changing technology choices. *Energy Policy* 34(3): 322–342.

<https://dx.doi.org/10.1016/j.enpol.2004.03.026>

FAO GeoNetwork. (2018). Find and analyze geo-spatial data. <http://www.fao.org/geonetwork/srv/en/main.home>. [Cited 20 Mar 2018].

Franco-Lopez H., Ek A. R., Bauer M. E. (2001). Estimation and mapping of forest stand density, volume, and cover type using the *k*-nearest neighbors method. *Remote Sensing of Environment* 77(3): 251–274.

[https://doi.org/10.1016/S0034-4257\(01\)00209-7](https://doi.org/10.1016/S0034-4257(01)00209-7)

GOFC-GOLD. (2016). A sourcebook of methods and procedures for monitoring and reporting anthropogenic greenhouse gas emissions and removals associated with deforestation, gains and losses of carbon stocks in forests remaining forests, and forestation. GOFC-GOLD Report version COP22-1, (GOFC-GOLD Land Cover Project Office, Wageningen University, The Netherlands). [http://www.gofcgold.wur.nl/redd/sourcebook/GOFC-GOLD\\_Sourcebook.pdf](http://www.gofcgold.wur.nl/redd/sourcebook/GOFC-GOLD_Sourcebook.pdf). [Cited 7 Nov 2017].

Google Earth. (2018). Gain a new perspective. [https://www.google.com/intl/en\\_uk/earth/](https://www.google.com/intl/en_uk/earth/). [Cited 3 Jan 2018].

Haapanen R. (2014). Feature extraction and selection in remote sensing-aided forest inventory. *Dissertationes Forestales* 181. 44 p.  
<https://dx.doi.org/10.14214/df.181>

Haapanen R., Tuominen S. (2008). Data Combination and Feature Selection for Multi-source Forest Inventory. *Photogrammetric Engineering & Remote Sensing* 74(7): 869–880.  
<https://doi.org/10.14358/PERS.74.7.869>

Haapanen R., Ek A. R., Bauer M. E., Finley A. O. (2004). Delineation of forest/nonforest land use classes using nearest neighbor methods. *Remote Sensing of Environment* 89: 265–271.  
<https://dx.doi.org/10.1016/j.rse.2003.10.002>

Halme M., Tomppo E. (2001). Improving the accuracy of multisource forest inventory estimates to reducing plot location error — a multicriteria approach. *Remote Sensing of Environment* 78(3):321–327.  
[https://doi.org/10.1016/S0034-4257\(01\)00227-9](https://doi.org/10.1016/S0034-4257(01)00227-9)

Häme T., Kilpi J., Ahola H. A., Rauste Y., Antropov O., Rautiainen M., Sirro L., Bounbone S. (2013a). Improved Mapping of Tropical Forests With Optical and SAR Imagery, Part I: Forest Cover and Accuracy Assessment Using Multi-Resolution Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 6(1): 74–91.  
<https://doi.org/10.1109/JSTARS.2013.2241019>

Häme T., Rauste Y., Antropov O., Ahola H. A., Kilpi J. (2013b). Improved Mapping of Tropical Forests With Optical and SAR Imagery, Part II: Above Ground Biomass Estimation. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 6(1): 92–101.  
<https://doi.org/10.1109/JSTARS.2013.2241020>

Haralick R. M., Shanmugam K., Dinstein I. (1973). Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics, SMC-3* (6): 610–621.

Hirvelä H., Härkönen K., Lempinen R., Salminen O. (2017). MELA2016: Reference Manual. Natural resources and bioeconomy studies 7/2017. 547 p. <http://urn.fi/URN:ISBN:978-952-326-358-1>. [Cited 27 Oct 2017].

Holmström H., Fransson J. E. S. (2003). Combining Remotely Sensed Optical and Radar Data in  $k$ NN-Estimation of Forest Variables. *Forest Science* 49(3):409–418. <https://doi.org/10.1093/forestscience/49.3.409>

Holmström H., Nilsson M., Ståhl G. (2001). Simultaneous Estimations of Forest Parameters using Aerial Photograph Interpreted Data and the  $k$  Nearest Neighbour Method. *Scandinavian Journal of Forest Research* 16(1): 67–78. <https://dx.doi.org/10.1080/028275801300004424>

Hopkinson C., Chasmer L., Gynan C., Mahoney C., Sitar M. (2016). Multisensor and Multispectral LiDAR Characterization and Classification of a Forest Environment. *Canadian Journal of Remote Sensing* 42(5): 501–520. <https://doi.org/10.1080/07038992.2016.1196584>

Hou Z., Xu Q., Tokola T. (2011). Use of ALS, Airborne CIR, and ALOS AVNIR-2 data for estimating tropical forest attributes in Lao PDR. *ISPRS Journal of Photogrammetry and Remote Sensing* 66(6): 776–786. <https://doi.org/10.1016/j.isprsjprs.2011.09.005>

Kangas A., Päivinen R., Holopainen M., Maltamo M. (2011). Metsän mittaus ja kartoitus, 3. edition. *Silva Carelica* 40. University of Eastern Finland, School of Forest Sciences. 210 p. [In Finnish].

Kangas A., Astrup R., Breidenbach J., Fridman J., Gobakken T., Korhonen K. T., Maltamo M., Nilsson M., Nord-Larsen T., Næsset E., Olsson H. (2018). Remote sensing and forest inventories in Nordic countries – roadmap for the future. *Scandinavian Journal of Forest Research* 33(4): 397–412. <https://doi.org/10.1080/02827581.2017.1416666>

Kärhä K. (2012). Comparison of two stump-lifting heads in final felling Norway spruce stand. *Silva Fennica* 46(4): 625–640. <https://doi.org/10.14214/sf.915>

Katila M., Tomppo E. (2001). Selecting estimation parameters for the Finnish multisource National Forest Inventory. *Remote Sensing of Environment* 76(1): 16–32. [https://doi.org/10.1016/S0034-4257\(00\)00188-7](https://doi.org/10.1016/S0034-4257(00)00188-7)

Katila M., Tomppo E. (2002). Stratification by ancillary data in multisource forest inventories employing  $k$ -Nearest Neighbour estimation. *Canadian Journal of Forest Research* 32: 1548–1561. <https://doi.org/10.1139/x02-047>

Katila M., Heikkinen J., Tomppo E. (2000). Calibration of small-area estimates for map errors in multisource forest inventory. *Canadian Journal of Forest Research* 30: 1329–1339.

<https://doi.org/10.1139/x99-234>

Kilkki P. (1984). Metsänmittausoppi. *Silva Carelica* 3. Joensuun yliopisto. Metsätieteellinen tiedekunta. 222 p. ISBN 951-696-512-1. [In Finnish].

Kilkki P., Päivinen R. (1987). Reference sample plots to combine field measurements and satellite data in forest inventory. Department of Forest Mensuration and Management, University of Helsinki. *Research Notes* 19: 209–215. ISBN 951-45-4207-X.

Koistinen A., Luiro J-P., Vanhatalo K. (eds.). (2016). Metsänhoidon suositukset energiapuun korjuuseen, työopas. [Recommendations for energy wood harvesting]. Forestry Development Centre Tapio. 78 p. [In Finnish]. <http://www.metsanhoitosuosituksset.fi/suosituksset/energiapuu/>. [Cited 19 Dec 2017].

Koivuniemi J., Korhonen K. T. (2006). Inventory by Compartments. In: Kangas A., Maltamo M. (eds). *Forest Inventory. Managing Forest Ecosystems* 10. Springer. pp. 271–278. [https://doi.org/10.1007/1-4020-4381-3\\_16](https://doi.org/10.1007/1-4020-4381-3_16)

Korhonen K.T., Ihalainen A., Viiri H., Heikkinen J., Henttonen H.M., Hotanen J.-P., Mäkelä H., Nevalainen S., Pitkänen J. (2013). Suomen metsät 2004–2008 ja niiden kehitys 1921–2008. *Metsätieteen aikakauskirja* 3/2013: 269–608. [In Finnish]. <http://www.metla.fi/aikakauskirja/ff133.htm>. [Cited 9 May 2018].

Laasasenaho, J. (1982). Taper curve and volume functions for pine, spruce and birch. *Communications Institutii Forestalis Fenniae* 108, 74 p.

Lappi J. (1992). JLP: A linear programming package for management planning. Finnish Forest Research Institute, *Research Papers* 414. 134 p. <http://urn.fi/URN:ISBN:951-40-1218-6>. [Cited 27 Oct 2017].

Lillesand T. M., Kiefer R. W., Chipman J. W. (2015). *Remote sensing and image interpretation*. Seventh Edition. Wiley. 736 p.

Lillesø J-P.B., Shrestha T.B., Dhakal L.P., Nayaju R.P., Shrestha R. (2005). The Map of Potential Vegetation of Nepal - a forestry/agro-ecological/biodiversity classification system. *Development and Environment Series 2-2005 and CFC-TIS Document Series No.110*. Forest & Landscape Denmark. <http://sl.ku.dk/rapporter/development-environment/>. [Cited 01 Mar 2018].

Luke. (2017). Luken tilastopalvelut. [In Finnish]. <http://www.metla.fi/metinfo/tilasto/khakuut/>. [Cited 23 Nov 2017].

Mäkelä H., Pekkarinen A. (2001). Estimation of timber volume at the sample plot level by means of image segmentation and Landsat TM imagery. *Remote Sensing of Environment* 77(1): 66–75. [https://doi.org/10.1016/S0034-4257\(01\)00194-8](https://doi.org/10.1016/S0034-4257(01)00194-8)

Mäkelä H., Hirvelä H., Nuutinen T., Kärkkäinen L. (2011). Estimating forest data for analyses of forest production and utilization possibilities at local-level by means of multi-source National Forest Inventory. *Forest Ecology and Management* 262: 1245–1359. <https://doi.org/10.1016/j.foreco.2011.06.027>

Mäkisara K., Katila M., Peräsaari J., Tomppo E. (2016). The Multi-Source National Forest Inventory of Finland – methods and results 2013. Natural Resources Institute Finland (Luke). Natural resources and bioeconomy studies 10/2016. <http://urn.fi/URN:ISBN:978-952-326-186-0>. [Cited 06 Aug 2018].

Malinen J. (2003). Locally adaptable non-parametric methods for estimating stand characteristics for wood procurement planning. *Silva Fennica* 37(1): 109–120. <https://doi.org/10.14214/sf.514>

Malinen J., Maltamo M., Harstela P. (2001). Application of Most Similar Neighbor Inference for Estimating Marked Stand Characteristics Using Harvester and Inventory Generated Stem Databases. *International Journal of Forest Engineering* 12(2): 33–41. <https://journals.lib.unb.ca/index.php/IJFE/article/view/9913/10098>. [Cited 21 Nov 2017].

Maltamo M., Packalen P. (2014) Species-Specific Management Inventory in Finland. In: Maltamo M., Næsset E., Vauhkonen J. (eds.). *Forestry Applications of Airborne Laser Scanning: Concepts and Case Studies. Managing Forest Ecosystems 27*. Springer. p. 241–252. [https://doi.org/10.1007/978-94-017-8663-8\\_12](https://doi.org/10.1007/978-94-017-8663-8_12)

Maltamo M., Næsset E., Bollandsås O. M., Gobakken T., Packalén P. (2009). Non-parametric prediction of diameter distributions using airborne laser scanner data. *Scandinavian Journal of Forest Research* 24(6): 541–553. <https://doi.org/10.1080/02827580903362497>

Mather P. M. (1987). *Computer Processing of Remotely-Sensed Images: An Introduction*. John Wiley & Sons. 352 p. ISBN 0 471 90648 4.

Mattila E. (1985). The combined use of systematic field and photo samples in a large-scale forest inventory in North Finland. *Communicationes Instituti Forestalis Fenniae* 131: 1–97. <http://urn.fi/URN:ISBN:951-40-0702-6>. [Cited 10 May 2018].

McRoberts R. E. (2008). Using satellite imagery and the k-nearest neighbors technique as a bridge between strategic and management forest inventories. *Remote Sensing of Environment* 112(5): 2212–2221. <https://doi.org/doi:10.1016/j.rse.2007.07.025>

McRoberts R. E. (2009). Diagnostic tools for nearest neighbors techniques when used with satellite imagery. *Remote Sensing of Environment* 113(3): 489–499. <https://doi.org/doi:10.1016/j.rse.2008.06.015>

McRoberts, R. E. (2012). Estimating forest attribute parameters for small areas using nearest neighbors techniques. *Forest Ecology and Management* 272: 3–12.

<https://doi.org/10.1016/j.foreco.2011.06.039>

McRoberts R. E., Tomppo E. O. (2007). Remote sensing support for national forest inventories. *Remote Sensing of Environment* 110(4): 412–419.

<https://doi.org/10.1016/j.rse.2006.09.034>

McRoberts R. E., Næsset E., Gobakken T. (2015). Optimizing the k-Nearest Neighbors technique for estimating forest aboveground biomass using airborne laser scanning data. *Remote Sensing of Environment* 163: 13–22.

<https://dx.doi.org/10.1016/j.rse.2015.02.026>

Metsätieto (2015). Metsätieto 2020 – Tavoitetila. 25.6.2015. Arbonaut Oy. [In Finnish]. <http://mmm.fi/documents/1410837/1504826/.../d3e572a8-eb0b-4715-80ac-fe04dc45b2ca>. [Cited 14 Nov 2017].

Moeur M., Stage A. R. (1995). Most similar neighbor: an improved sampling inference procedure for natural resource planning. *Forest Science* 41(2): 337–359.

Morales-Barquero L., Skutsch M., Jardel-Peláez E. J., Ghilardi A., Kleinn C., Healey J. R. (2014). Operationalizing the Definition of Forest Degradation for REDD+, with Application to Mexico. *Forests* 5(7): 1653–1681.

<https://dx.doi.org/10.3390/f5071653>

Muinonen E., Tokola T. (1990). An application of remote sensing for communal forest inventory. In: *Proceedings from SNS/IUFRO Workshop in Umeå. 26–28 February 1990. Remote Sensing Laboratory, Swedish University of Agricultural Sciences, Umeå Report 4*, p. 35–42. ISBN 91-576-4208-7.

Mustonen J., Packalén P., Kangas A. (2008). Automatic segmentation of forest stands using a canopy height model and aerial photography. *Scandinavian Journal of Forest Research* 23(6): 534–545.

<https://doi.org/10.1080/02827580802552446>

Næsset E. (2014). Area-Based Inventory in Norway – From Innovation to an Operational Reality. In: Maltamo M., Næsset E., Vauhkonen J. (eds.). *Forestry Applications of Airborne Laser Scanning: Concepts and Case Studies. Managing Forest Ecosystems 27*. Springer. p. 215–240.

[https://doi.org/10.1007/978-94-017-8663-8\\_11](https://doi.org/10.1007/978-94-017-8663-8_11)

Næsset E., Bollandsås O. M., Gobakken T., Gregoire T. G., Ståhl G. (2013a). Model-assisted estimation of change in forest biomass over an 11 year period in a sample survey supported by airborne LiDAR: A case study with post-stratification to provide “activity data”. *Remote Sensing of Environment* 128: 299–314.

<https://dx.doi.org/10.1016/j.rse.2012.10.008>

Næsset E., Gobakken T., Bollandsås O. M., Gregoire T.G., Nelson R., Ståhl G. (2013b). Comparison of precision of biomass estimates in regional field sample surveys and airborne

LiDAR-assisted surveys in Hedmark County, Norway. *Remote Sensing of Environment* 130: 108–120.

<https://doi.org/10.1016/j.rse.2012.11.010>

Neteler M., Mitasova H. (2008). *Open Source GIS: A GRASS GIS Approach*. 3rd edn. Springer, New York. 406 p. ISBN 978-0-387-35767-6.

Nilsson M., Nordkvist K., Jonzén J., Lindgren N., Axensten P., Wallerman J., Egberth M., Larsson S., Nilsson L., Eriksson J., Olsson H. (2017). A nationwide forest attribute map of Sweden predicted using airborne laser scanning data and field data from the National Forest Inventory. *Remote Sensing of Environment* 194: 447–454.

<https://dx.doi.org/10.1016/j.rse.2016.10.022>

Olofsson P., Foody G. M., Herold M., Stehman S. V., Woodcock C. E., Wulder M. A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment* 148: 42–57.

<https://dx.doi.org/10.1016/j.rse.2014.02.015>

Pachana P. (2016). Forest stands volume estimation by using Finnish Multi-Source National Forest Inventory in Stołowe Mountains National Park. *Folia Forestalia Polonica, series A* 58 (1): 3–12. DOI: 10.1515/ffp-2016-0001.

Packalén P., Maltamo M. (2007). The k-MSN method for the prediction of species-specific stand attributes using airborne laser scanning and aerial photographs. *Remote Sensing of Environment* 109(3): 328–341.

<https://doi.org/10.1016/j.rse.2007.01.005>

Packalén P., Suvanto A., Maltamo M. (2009). A Two Stage Method to Estimate Species-specific Growing Stock. *Photogrammetric Engineering & Remote Sensing* 75(12): 1451–1460.

<https://doi.org/10.14358/PERS.75.12.1451>

Pekkarinen A. (2002). Image segment-based spectral features in the estimation of timber volume. *Remote Sensing of Environment* 82(2–3): 349–359.

[https://dx.doi.org/10.1016/S0034-4257\(02\)00052-4](https://dx.doi.org/10.1016/S0034-4257(02)00052-4)

Peltola A., Ihalainen A. (2012). Forest resources. In: Ylitalo E. (ed.). *Finnish Statistical Yearbook of Forestry*. p. 37–78.

Peres C. A., Barlow J., Laurance W. F. (2006). Detecting anthropogenic disturbance in tropical forests. *Trends in Ecology and Evolution* 21(5): 227–229.

<https://dx.doi.org/10.1016/j.tree.2006.03.007>

Peuhkurinen J., Maltamo M., Malinen J. (2008a). Estimating species-specific height diameter distributions and saw log recoveries from ALS data and aerial photographs: A distribution-based approach. *Silva Fennica* 42(4): 625–641.

<https://doi.org/10.14214/sf.237>



Peuhkurinen J., Maltamo M., Vesa L., Packalén P. (2008b). Estimation of Forest Stand Characteristics Using Spectral Histograms Derived from an Ikonos Satellite Image. *Photogrammetric Engineering and Remote Sensing* 74(11): 1335–1341. <https://doi.org/10.14358/PERS.74.11.1335>

Ploton P., Barbier N., Couteron P., Antin C.M., Ayyappan N., Balachandran N., Barathan N., Bastin J.-F., Chuyong G., Dauby G., Droissart V., Gastellu-Etchegorry J.-P., Kamdem N.G., Kenfack D., Libalah M., Mofack G., Momo S.T., Pargal S., Petronelli P., Proisy C., Réjou-Méchain M., Sonké B., Texier N., Thomas D., Verley P., Zebaze Dongmo D., Berger U., Péliissier R. (2017). Toward a general tropical forest biomass prediction model from very high resolution optical satellite images. *Remote Sensing of Environment* 200: 140–153. <http://dx.doi.org/10.1016/j.rse.2017.08.001>

Poso S. (1972). A method of combining photo and field samples in forest inventory. *Communicationes Instituti Forestalis Fenniae* 76(1): 1–133. <http://urn.fi/URN:NBN:fi-metla-201207171108>. [Cited 10 May 2018].

Poso S., Kujala M. (1971). Ryhmitetty ilmakuva- ja maasto-otanta Inarin, Utsjoen ja Enontekiön metsien inventoinnissa. Summary: A two-phase forest inventory method based on photo and field plot samplings as applied in Northernmost Lapland. *Folia Forestalia* 132: 1–40. <http://urn.fi/URN:NBN:fi-metla-201207191799>. [Cited 10 May 2018].

Pukkala T. (1994). *Metsäsuunnittelun perusteet*. Gummerus Kirjapaino Oy Jyväskylä. 242 p. ISBN 952-90-5784-9. [In Finnish].

QGIS. (2017). QGIS A Free and Open Source Geographic Information System. <http://www.qgis.org/en/site/>. [Cited 22 Nov 2017].

R Core Team. (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>. [Cited 22 Nov 2017].

Repola J. (2008). Biomass equations for birch in Finland. *Silva Fennica* 42(4): 605–624. <https://doi.org/10.14214/sf.236>

Repola J. (2009). Biomass equations for Scots pine and Norway spruce in Finland. *Silva Fennica* 43(4): 625–647. <https://doi.org/10.14214/sf.184>

Satellite Imaging Corporation. (2017). *Satellite Sensors*. <https://www.satimagingcorp.com/satellite-sensors/>. [Cited 29 Nov 2017].

Siitonen M., Härkönen K., Hirvelä H., Jämsä J., Kilpeläinen H., Salminen O., Teuri M. (1996). *Mela handbook 1996 edition*. Research Paper 622. The Finnish Forest Research Institute. 452 p.

Smeets E.M.W., Faaij A.P.C. (2007). Bioenergy potentials from forestry in 2050. An assessment of the drivers that determine the potentials. *Climatic Change* 81: 353–90.

<https://doi.org/10.1007/s10584-006-9163-x>

Stehman S. V. (1997). Selecting and Interpreting Measures of Thematic Classification Accuracy. *Remote Sensing of Environment* 62(1): 77–89.  
[https://doi.org/10.1016/S0034-4257\(97\)00083-7](https://doi.org/10.1016/S0034-4257(97)00083-7)

St-Onge B., Cavayas F. (1995). Estimating forest stand structure from high resolution imagery using the directional variogram. *International Journal of Remote Sensing* 16(11): 1999–2021.  
<https://doi.org/10.1080/01431169508954535>

St-Onge B., Cavayas F. (1997). Automated Forest Structure Mapping from High Resolution Imagery Based on Directional Semivariogram Estimates. *Remote Sensing of Environment* 61(1): 82–95.  
[https://doi.org/10.1016/S0034-4257\(96\)00242-8](https://doi.org/10.1016/S0034-4257(96)00242-8)

Tesfamichael S.G., Ahmed F., van Aardt J.A.N., Blakeway F. (2009). A semi-variogram approach for estimating stems per hectare in Eucalyptus grandis plantations using discrete-return lidar height data. *Forest Ecology and Management* 258(7): 1188–1199.  
<https://doi.org/10.1016/j.foreco.2009.06.016>

Tokola T. (2000). The Influence of Field Sample Data Location on Growing Stock Volume Estimation in Landsat TM-Based Forest Inventory in Eastern Finland. *Remote Sensing of Environment* 74(3): 422–431.  
[https://doi.org/10.1016/S0034-4257\(00\)00135-8](https://doi.org/10.1016/S0034-4257(00)00135-8)

Tokola T. (2015). Remote Sensing Concepts and Their Applicability in REDD+ Monitoring. *Current Forestry Reports* 1(4): 252–260.  
<https://doi.org/10.1007/s40725-015-0026-4>

Tokola T., Heikkilä J. (1997). Improving Satellite Image Based Forest Inventory by Using A Priori Site Quality Information. *Silva Fennica* 31(1): 67–78.  
<https://doi.org/10.14214/sf.a8511>

Tokola T., Pitkänen J., Partinen S., Muinonen E. (1996). Point accuracy of a non-parametric method in estimation of forest characteristics with different satellite materials. *International Journal of Remote Sensing* 17(12): 2333–2351.  
<https://doi.org/10.1080/01431169608948776>

Tomppo E. (1996). Multi-source National Forest Inventory of Finland. *New Thrusts in Forest Inventory. Proceedings of IUFRO XX World Congress, 6-12 Aug 1995, Tampere, Finland.* EFI Proceedings 7. p. 27–41. European Forest Institute. ISBN 952-9844-15-8.

Tomppo E. (2006a). The Finnish National Forest Inventory. In: Kangas A., Maltamo M. (eds.). *Forest Inventory – Methodology and Applications. Managing Forest Ecosystems* 10. Springer. p. 179–194.  
<https://doi.org/10.1007/1-4020-4381-3>

Tomppo E. (2006b). The Finnish Multi-source National Forest Inventory - Small Area Estimation and Map Production. In: Kangas A., Maltamo M. (eds.). *Forest Inventory – Methodology and Applications. Managing Forest Ecosystems 10*. Springer. p. 195–224. <https://doi.org/10.1007/1-4020-4381-3>

Tomppo, E., Halme, M. (2004). Using coarse scale forest variables as ancillary information and weighting of variables in k-NN estimation: a genetic algorithm approach. *Remote Sensing of Environment* 92(1): 1–20. <https://doi.org/10.1016/j.rse.2004.04.003>

Tomppo E., Katila M., Moilanen J., Mäkelä H., Peräsaari J. (1998). Kunnittaiset metsävaratiedot 1990–94. *Metsätieteen aikakauskirja – Folia Forestalia 4B/1998*. p. 619–839. [In Finnish]. <https://doi.org/10.14214/ma.6453>

Tomppo E., Goulding C., Katila M. (1999). Adapting Finnish Multi-Source Forest Inventory Techniques to the New Zealand Preharvest Inventory. *Scandinavian Journal of Forest Research* 14(2): 182–192. <https://doi.org/10.1080/02827589950152917>

Tomppo E., Haakana M., Katila M. Peräsaari J. (2008a). *Multi-Source National Forest Inventory – Methods and Applications. Managing Forest Ecosystems 18*. Springer. New York. 374 p.

Tomppo E., Olsson H., Ståhl G., Nilsson M., Hagner O. & Katila M. (2008b). Combining national forest inventory field plots and remote sensing data for forest databases. *Remote Sensing of Environment* 112(5): 1982–1999. <https://doi.org/10.1016/j.rse.2007.03.032>

Tomppo E., Haakana M., Katila M., Mäkisara K., Peräsaari J. (2009a). The Multi-source National Forest Inventory of Finland – methods and results 2005. *Metlan työraportteja / Working Papers of the Finnish Forest Research Institute 111*. 277 p. ISBN 978-951-40-2151-0 (PDF). <http://www.metla.fi/julkaisut/workingpapers/2009/mwp111.htm>. [Cited 6 Oct 2017].

Tomppo E. O., Gagliano C., De Natale F., Katila M., McRoberts R. E. (2009b). Predicting categorical forest variables using an improved k-Nearest Neighbour estimator and Landsat imagery. *Remote Sensing of Environment* 113(3): 500–517. <https://doi.org/10.1016/j.rse.2008.05.021>

Tomppo E., Katila M., Mäkisara K., Peräsaari J., Malimbwi R., Chamuya N., Otieno J., Dalsgaard S., Leppänen M. (2010). A Report to the Food and Agriculture Organization of the United Nations (FAO) in Support of Sampling Study for National Forestry Resources Monitoring and Assessment (NAFORMA) in Tanzania; FAO: Rome, Italy, 10 March 2010. <http://www.mp-discussion.org/NAFORMA.pdf>. [Cited 24 Aug 2012].

Tomppo E., Katila M., Mäkisara K., Peräsaari J. (2012). *The Multi-source National Forest Inventory of Finland – methods and results 2007. Metlan työraportteja / Working Papers of*

the Finnish Forest Research Institute 227. 233 p. ISBN 978-951-40-2357-6 (PDF). <http://www.metla.fi/julkaisut/workingpapers/2012/mwp227.htm>. [Cited 6 Oct 2017].

Tomppo E., Malimbwi R., Katila M., Mäkisara K., Henttonen H. M., Chamuya N., Zahabu E., Otieno J. (2014). A sampling design for a large area forest inventory: case Tanzania. *Canadian Journal of Forest Research* 44(8): 931–948. <https://doi.org/10.1139/cjfr-2013-0490>

Torvelainen J. (2010). Harvesting and transportation of roundwood. In: Ylitalo E. (ed.). *Finnish Statistical Yearbook of Forestry*. p. 195–214.

Treitz P. (2001). Variogram analysis of high spatial resolution remote sensing data: An examination of boreal forest ecosystems. *International Journal of Remote Sensing* 22 (18): 3895–3900. <https://doi.org/10.1080/01431160110069890>

Tuominen S., Pekkarinen A. (2004). Local radiometric correction of digital aerial photographs for multi source forest inventory. *Remote Sensing of Environment* 89(1): 72–82. <https://doi.org/10.1016/j.rse.2003.10.005>

Tuominen S., Eerikäinen K., Schibalski A., Haakana M., Lehtonen A. (2010). Mapping biomass variables with a multi-source forest inventory technique. *Silva Fennica* 44(1):109–119. article id 458. <https://doi.org/10.14214/sf.458>

USGS. (2018). MODIS Products Table. [https://lpdaac.usgs.gov/dataset\\_discovery/modis/modis\\_products\\_table](https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table). [Cited 20 Mar 2018].

USGS Landsat Missions. (2017). Landsat Missions. <https://landsat.usgs.gov>. [Cited 17 Nov 2017].

Valbuena R. (2014). Integrating Airborne Laser Scanning with Data from Global Navigation Satellite Systems and Optical Sensors. In: Maltamo M., Næsset E., Vauhkonen J. (eds.). *Forestry Applications of Airborne Laser Scanning: Concepts and Case Studies*. *Managing Forest Ecosystems* 27. Springer. p. 63–88. [https://doi.org/10.1007/978-94-017-8663-8\\_4](https://doi.org/10.1007/978-94-017-8663-8_4)

Vis M.W., van den Berg D., Anttila M.P., Böttcher H., Dees M., Domac J., Eleftheriadis I., Gecevska V., Goltsev V., Gunia K., Kajba D., Koch B., Köppen S., Kunikowski G., Lehtonen A.H.S., Leduc S., Lemp D., Lindner M., Mustonen J., Paappanen T., Pekkanen J.M., Ramos C.I.S., Rettenmaier N., Schneider U.A., Schorb A., Segon V., Smeets E.M.W., Torén C.J.M., Verkerk P.J., Zheliezna T.A., Zibtsev S. (2010). Harmonization of biomass resource assessments, Volume I, Best Practices and Methods Handbook. 220 p. [https://www.researchgate.net/publication/268388401\\_Harmonization\\_of\\_biomass\\_resource\\_assessments\\_Volume\\_I\\_Best\\_Practices\\_and\\_Methods\\_Handbook](https://www.researchgate.net/publication/268388401_Harmonization_of_biomass_resource_assessments_Volume_I_Best_Practices_and_Methods_Handbook). [Cited 25 Oct 2017]. <https://doi.org/10.13140/2.1.4643.8084>

Wohletz G. (2011). A GIS Model to Estimate a Sustainable Potential of Forest Fuel for Energy Generation in the Municipality of Växjö, Sweden. Master's of Science Thesis in Geoinformatics. TRITA-GIT EX 11-005. School of Architecture and the Built Environment Royal Institute of Technology (KTH) Stockholm, Sweden. <https://www.diva-portal.org/smash/get/diva2:437226/FULLTEXT01.pdf>. [Cited 14 Nov 2017].

Wulder M. A., White J. C., Nelson R. F., Næsset E., Ørka H. O., Coops N. C., Hilker T., Bater C. W., Gobakken T. (2012). Lidar sampling for large-area forest characterization: A review. *Remote Sensing of Environment* 121: 196–209.  
<https://doi.org/10.1016/j.rse.2012.02.001>

Xu Q., Hou Z., Tokola T. (2012). Relative radiometric correction of multi-temporal ALOS AVNIR-2 data for the estimation of forest attributes. *ISPRS Journal of Photogrammetry and Remote Sensing* 68: 69–78.  
<https://doi.org/10.1016/j.isprsjprs.2011.12.008>