Norwegian University of Life Sciences
Faculty of Environmental Sciences and
Natural Resource Management

Philosophiae Doctor (PhD)
Thesis 2017:53

Fusion of airborne laser scanning and hyperspectral data for predicting forest characteristics at different spatial scales

Kombinasjon av flybåren laserscanning og hyperspektrale data for prediksjon av skoglige egenskaper på ulik romlig skala

Kaja Kandare

Fusion of airborne laser scanning and hyperspectral data for predicting forest characteristics at different spatial scales

Kombinasjon av flybåren laserscanning og hyperspektrale data for prediksjon av skoglige egenskaper på ulik romlig skala

Philosophiae Doctor (PhD) Thesis

Kaja Kandare

Faculty of Environmental Sciences and Natural Resource Management
Norwegian University of Life Sciences

Ås 2017

Thesis number 2017:53
ISSN 1894-6402
ISBN 978-82-575-1452-5

PhD supervisors

Dr. Hans Ole Ørka
Faculty of Environmental Sciences and Natural Resource Management
Norwegian University of Life Sciences
P.O. Box 5003, NMBU, NO-1432 Ås, Norway

Dr. Michele Dalponte
Department of Sustainable Agro-Ecosystems and Bioresources
Research and Innovation Centre, Fondazione Edmund Mach
Via E. Mach 1, 38010 San Michele all'Adige (TN), Italy

Professor Erik Næsset
Faculty of Environmental Sciences and Natural Resource Management
Norwegian University of Life Sciences
P.O. Box 5003, NMBU, NO-1432 Ås, Norway

Evaluation committee

Dr. Valerie A. Thomas
Department of Forest Resources and Environmental Conservation
Virginia Polytechnic Institute and State University
307A Cheatham Hall, Blacksburg, VA 24061, USA

Dr. Petteri Packalén
School of Forest Sciences
University of Eastern Finland
P.O. Box 111, FI-80101 Joensuu, Finland

Professor Hans Fredrik Hoen
Faculty of Environmental Sciences and Natural Resource Management
P.O. Box 5003, NMBU, NO-1432 Ås, Norway

Preface

This thesis has been submitted to the Faculty of Environmental Sciences and Natural Resource Management, Norwegian University of Life Sciences, as a part of my PhD studies. The approval of this thesis, academic training, trial lecture, and public defense are four main components to obtain the Doctor of Philosophy degree. My doctoral studies were funded with support from Fondazione Edmund Mach.

I would not have succeeded to produce this thesis without strong scientific backing of my main-supervisor Dr. Hans Ole Ørka and co-supervisor Dr. Michele Dalponte throughout my PhD studies. They both helped me to design my PhD project, showed me how to organize the scientific work, and guided me continuously until the objectives were achieved. Thank you for always being around and ready for my thoughts and discussions. I also thank my co-supervisor Prof. Erik Næsset for his good suggestions, ideas, and comments on my work.

My sincere thanks go to Damiano Gianelle, Samantha Riccadonna, Pietro Franceschi and other colleges at the Foundation Edmund Mach, Trento for their scientific support. I am also grateful to all the co-authors of the articles and scientific advice.

I am grateful to all fellow colleagues and friends in Italy and Norway for their advice, discussions, ideas, encouragements, and their company during my PhD. I am especially thankful to my friends Viktor Strimbu and Urska Vrhovsek for their moral support.

I am grateful to my loving mother Franciska Kandare and father Srecko Kandare for their continued support. Most importantly, my heartfelt thanks goes to my partner Miha Ilovar, who always encouraged and waited for me to accomplish the mission.

Kaja Kandare,
May 2017, Trento

Contents

Preface iii

Abstract vii

List of papers ix

Synopsis 1

1 Introduction 3

2 Background 7

2.1 Airborne laser scanning (ALS) data 7

2.2 Airborne hyperspectral data 9

2.3 ITC approach and delineation algorithm 11

2.4 Semi-ITC approach 13

2.5 ABA approach 13

2.6 Fusion of ALS and hyperspectral data 14

2.7 Forest characteristics investigated in this thesis 15

3 Material 15

3.1 Study areas 15

3.1.1 Pellizzano 16

3.1.2 Våler 16

3.2 Field data 18

3.2.1 Pellizzano 18

3.2.2 Våler 18

3.3 ALS and hyperspectral data 19

3.3.1 Pellizzano 19

3.3.2 Våler 19

4 Methods 20

5 Major findings 22

5.1 Quantification of influence of forest structure and ALS point cloud density on established ITC delineation algorithm (Paper I) 22

5.2 Improvement of site index maps using ITC approach together with fused ALS and hyperspectral data (Paper II) 22

5.3 Evaluation of the performance of three remotely sensed-based forest inventory approaches to assess how different spatial details influenced the predictions of species-specific volume using fused ALS and hyperspectral data (Paper III) 23

5.4 Investigate the benefits of ALS and hyperspectral data, separately and fused, to predict forest structural measures (Paper VI) 24

6 Discussion 24

6.1 Fusion of ALS and hyperspectral data (Papers II, III, IV) 24

6.2 Exploring different spatial scales in the prediction of forest characteristics (Papers I, II, III) 27

7 Conclusion and further perspectives 30

References 31

APPENDIX: Papers I - IV

Abstract

Forests can be characterized by many attributes such as mean height, volume, diameter at breast height (DBH), age, tree species distribution, and different indices describing productivity and diversity. All these characteristics can be estimated using a wide range of remote sensing data from aerial photography and airborne laser scanning (ALS) to spaceborne or airborne multispectral or hyperspectral sensors, etc. Remote sensing is a science to obtain information of objects without making any physical contact with it, typically from aircraft or satellites. In particular, this thesis focused on two remotely sensed data sources that at the moment seem to be the most promising for abovementioned purposes: ALS and airborne hyperspectral data. Their combined use or fusion can be beneficial as they provide a complementary information for characterizing forest attributes. ALS and hyperspectral technologies provide very high spatial resolution allowing us to map the forest attributes at a very high spatial detail. This can be useful for certain applications but increasing the spatial detail does not always improve the accuracy of the predictions. Indeed, many predicted forest characteristics can be explored at many spatial scales, e.g. from tree to stand. Thus, the major objective of this thesis was to evaluate the potential of fusing ALS and hyperspectral data for the prediction of forest characteristics and to evaluate the benefits of different spatial details in the prediction of such characteristics. The fusion of ALS and hyperspectral data and the spatial scale exploration were carried out simultaneously in this thesis, and in particular it started with a focus on the spatial scale (development of a new ITC delineation algorithm) and it finished with a focus only on data fusion (prediction of forest structural diversity measures).

The ALS and hyperspectral data were fused at two different levels, product and variable-level fusion. The product-level fusion was used for the prediction of the site index and species-specific volume, while the variable-level fusion was used for total and species-specific volume, as well as structural diversity measures. For the evaluation of different spatial details in the prediction of forest characteristics we considered three remotely sensed-based inventory approaches, namely the individual tree crown (ITC) approach, the semi-ITC approach, and the area-based approach (ABA). In order to apply the ITC and semi-ITC approaches, the individual tree delineation algorithm was needed and developed based on the ALS point cloud. The forest characteristics evaluated in this thesis were: individual tree attributes (such as tree height, DBH, stem volume, age, and species), forest attributes (such as site index, total and species-specific volume), and forest structural diversity measures.

The ITC approach allowed an accurate determination of the height, species, DBH, and stem volume, while the age was subject to a greater error. The ITC approach for site index determination in combination with ALS and hyperspectral data was found to be an efficient and a stable procedure and it reached similar accuracy as in the existing site index maps based on field surveys. For species-specific volume, the ITC approach reached high accuracies but there were also large systematic errors for minority species. For majority species, the semi-ITC approach resulted in slightly higher accuracies and smaller systematic errors compared to ABA. In all three approaches, ALS and hyperspectral data were

important to provide higher accuracies. The fusion of ALS and hyperspectral data for forest structural diversity measures did not improve their accuracy but produced accuracy levels comparable to the models built on ALS data alone, except for one measure. In these experiments, ALS data showed the best predictions for the majority of the structural diversity measures taken into account.

To conclude, the ITC and semi-ITC approaches can provide higher spatial detail of the predicted forest characteristics. This information can also be aggregated to coarser scales, e.g. stands. The use of ITC and semi-ITC approaches has a potential in different forestry and ecology applications, where the accuracy of the semi-ITC also showed the capacity in operational forest applications. The fusion of ALS and hyperspectral data improves the predictions of forest characteristics, such as volumes and site index, while for some forest structural diversity measures the fusion did not improve the accuracy of results. Fusion of such data, especially for structural diversity measures has to be further explored.

List of papers

I. Kandare, K., Ørka, H. O., Chan, J. C. W., & Dalponte, M. (2016). Effects of forest structure and airborne laser scanning point cloud density on 3D delineation of individual tree crowns. *European Journal of Remote Sensing*, 49, 337–359. http://doi.org/10.5721/EuJRS20164919

II. Kandare, K., Ørka, H. O., Dalponte, M., Næsset, E., & Gobakken, T. (2017). Individual tree crown approach for predicting site index in boreal forests using airborne laser scanning and hyperspectral data. *International Journal of Applied Earth Observation and Geoinformation*, 60, 72–82. http://doi.org/10.1016/j.jag.2017.04.008

III. Kandare, K., Dalponte, M., Ørka, H., Frizzera, L., & Næsset, E. (2017). Prediction of species-specific volume using different inventory approaches by fusing airborne laser scanning and hyperspectral data. *Remote Sensing*, 9(5). http://doi.org/10.3390/rs9050400

IV. Kandare, K., Riccadonna, S., Franceschi, P., Ørka, H. O., Dalponte, M., (manuscript). Fusion of airborne laser scanning and hyperspectral data for assessing forest structural diversity indices

Synopsis

1 Introduction

Forest structure can be characterized by many biophysical attributes such as canopy cover, stem density, basal area, mean height, volume, diameter at breast height (DBH), age, biomass, and tree species distribution (Dalponte et al., 2014; Hakkenberg et al., 2016; Hernández-Stefanoni et al., 2014; Listopad et al., 2015; M Maltamo et al., 2009). Additionally, such forest characteristics are a key element for retrieving information on site productivity, forest structural diversity, richness of wildlife communities, wildfire behavior, etc. (Guo et al., 2017; Hill and Hinsley, 2015; Kandare et al., 2017b; McElhinny et al., 2005; Riaño, 2003). Thus, accurate and reliable measurements of forest characteristics are important for sustainable forest management to enable forest managers, silviculturists, and ecologists to make sound decisions in a variety of applications.

Silvicultural practices and natural events such as landslides, wildfires, drought, and insect outbreaks alter stand composition and structure. Therefore, frequent updates of forest attributes are requested. Nowadays, remote sensing data are commonly used to describe, predict, and assess forests attributes and they can provide important knowledge to support national forest inventories (McRoberts and Tomppo, 2007) and for conservation monitoring (Nagendra et al., 2013). Furthermore, the remote sensing technologies, such as aerial photography, spaceborne or airborne laser scanning, spaceborne or airborne multispectral and hyperspectral images, and synthetic aperture radar (SAR), enable observation of forest areas at different temporal and geographical scales (Eitel et al., 2016; Fassnacht et al., 2016; Latifi et al., 2015; White et al., 2016; Yu et al., 2015). Among all the available remote sensing data, this thesis focuses on airborne laser scanning (ALS) and airborne hyperspectral data. Airborne sensors were shown to be effective in covering large areas with high detail. Among the mentioned sensors, ALS and airborne hyperspectral data are at the moment the most interesting sources for characterizing forests. In particular, ALS is a key source providing a three-dimensional (3D) point cloud, which appears as dense xyz coordinates (Figure 1). ALS data have shown to produce accurate estimates compared to other remote sensing techniques for forest biophysical attributes (e.g. volume, height, DBH, crown area, and stem density) (Hollaus et al., 2006; Holmgren, 2004; Kankare et al., 2013; Næsset, 2002; Næsset and Økland, 2002; Wing et al., 2012; Yu et al., 2015). For identifying tree species, airborne hyperspectral images (Figure 2) are a very promising data source due to their ability to detect subtle variations in the chemical and structural properties of the tree canopy. In such images, radiance data are available for many narrow contiguous bands (>50), from the visible to the near-infrared part of the spectrum. Due to its high spectral resolution, hyperspectral imagery was found to be superior for the classification of tree species compared to multispectral imagery

(Dalponte et al., 2012; Ørka et al., 2013). Currently, the fusion of ALS and hyperspectral data sources is the most promising approach to improve the accuracy of models predicting species-specific biophysical attributes and various forest characteristics, i.e. forest structural diversity (Ørka et al., 2013; Torabzadeh et al., 2014).

In forestry and ecology studies, sample plots are generally established in order to relate field and remote sensing data. Field data collection is carried using sample plots distributed over an area of interest, and can follow different strategies (e.g. stratified sampling, random sampling, etc.). After co-registering sample plots and remote sensing data, several metrics or variables can be extracted from ALS and hyperspectral data for each sample plot. Subsequently, these variables are used to construct statistical relationships with field-observed forest attributes. The relationships, typically in the form of regression models, are then used to predict forest attributes for a grid-cell size of the same size as the sample plots. Such approach refers to the area-based approach (ABA) (Næsset, 2002).

To increase the spatial detail, individual trees can be detected within a sample plot and forest characteristics can be provided for each tree. Such approach is called the individual tree crown (ITC) approach and it was introduced by Hyyppä and Inkinen (1999). Based on an ALS point cloud or a spectral image, crown segments, often referred to as ITCs, are detected and delineated applying a segmentation algorithm (Eysn et al., 2015; Ke and Quackenbush, 2011; Wang et al., 2016). Each crown segment is matched with one field-observed tree as the ITC approach presumes that one crown segment contains exclusively one field-observed tree. For each crown segment, various ALS- and spectral-derived variables are extracted, such as ALS maximum height, crown area, spectral mean band values and spectral indices. Based on these variables, the biophysical attributes, such as species, volume, age, and DBH can be predicted for each crown segment, and can be aggregated to any grid-cell size or other scales, e.g. to a forest stand. The detection accuracy of the ITC approach is usually measured with omission error (failure to detect a tree or segmenting multiple trees into a single crown segment) and commission error (detecting an object that is not a tree or splitting a single tree into multiple crown segments). Omission error usually leads to underprediction of the forest attributes. This is a common problem as delineation algorithms tend to not detect all the trees within an area of interest. To reduce these errors, the semi-ITC approach has been proposed (Breidenbach et al., 2010), which is equivalent to the ITC approach -regarding the delineation algorithm and remote sensing variables extraction- but it has a different matching procedure. In contrast to the ITC approach, the semi-ITC approach allows a crown segment to contain, beside none and one, also multiple field-observed trees. Forest characteristics for each crown segment are obtained by relating field measurements of trees and remote sensing variables of crown segments to develop prediction models. The work presented in this thesis combines ALS and hyperspectral data by adopting the three aforementioned inventory approaches (ABA, ITC, and semi-ITC) for the prediction of various forest characteristics.

State of the art remote sensing data acquired from airborne platforms are characterized by a high spatial resolution (<1 m), which can improve the spatial scale of forest characteristics' predictions on maps (with the spatial scale of interest either being an individual tree, a stand, or a region). If the spatial detail of forest characteristics estimations improve different communities, ecologists, forest managers, and forest users are able to use this enhanced information in their activities related to natural resource policy and planning, forest management and conservation, biodiversity, and ecology.

Several forest characteristics (tree heights, tree positions, tree species, DBH, stem volume, site index, and forest structural diversity measures) should be investigated, and innovative inventory approaches should be explored to evaluate whether the increase of spatial detail is possible. In particular, the development of an ITC delineation method would allow to obtain refined maps at a smaller grid size, if the ITC and semi-ITC approaches are able to provide accurate predictions of forest characteristics. Moreover, the comparison among the ITC, semi-ITC, and ABA approaches at the grid-cell level should be further investigated to evaluate the accuracy of forest characteristics obtained with each approach. In many studies, forest characteristics are generally predicted with only one type of remotely sensed data. Thus, the synergy among different data sources appears to be a key step to achieve greater accuracy in the prediction of forest characteristics. In particular, ALS and hyperspectral data provide complementary and independent information: one related to the forest 3D structure and one to the spectral characteristics of the forest. In this context, the efficiency of such data synergy needs to be further investigated.

The major objectives of this thesis were to evaluate the potential of fusing ALS and airborne hyperspectral data (Papers II, III, IV) for the prediction of forest attributes and to explore different spatial levels in the prediction of biophysical attributes (Papers I, II, III). The specific objectives were: 1) to establish a 3D ITC delineation method and to quantify the influence of forest structure and airborne laser scanning point cloud density on the ITC delineation algorithm (Paper I), 2) to improve the existing site index maps by applying the developed ITC delineation method together with fused ALS and hyperspectral data (Paper II), 3) to predict species-specific volume using fused ALS and hyperspectral data in order to analyze the performance of three remotely sensed-based forest inventory approaches to assess how different spatial details influenced the results (Paper III), 4) to predict forest structural diversity with ALS and hyperspectral data, separately and fused, in order to investigate the benefits of each data source (Paper IV). The illustration of relationship between papers, and major and specific objectives is summarized in Figure 3.

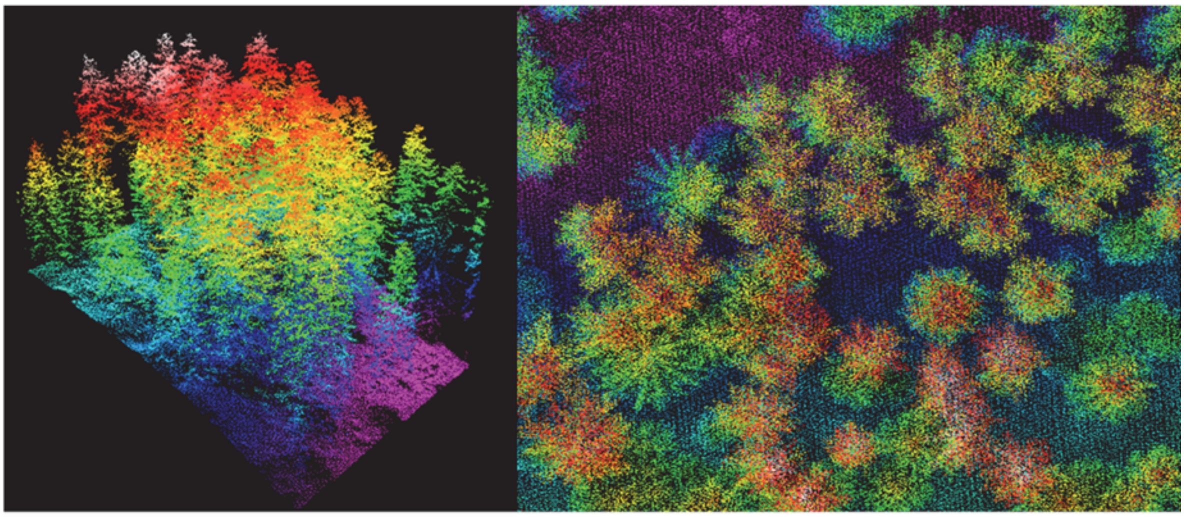

Figure 1: Example of ALS point cloud in forest area.

Figure 2: Example of hyperspectral image over forest area.

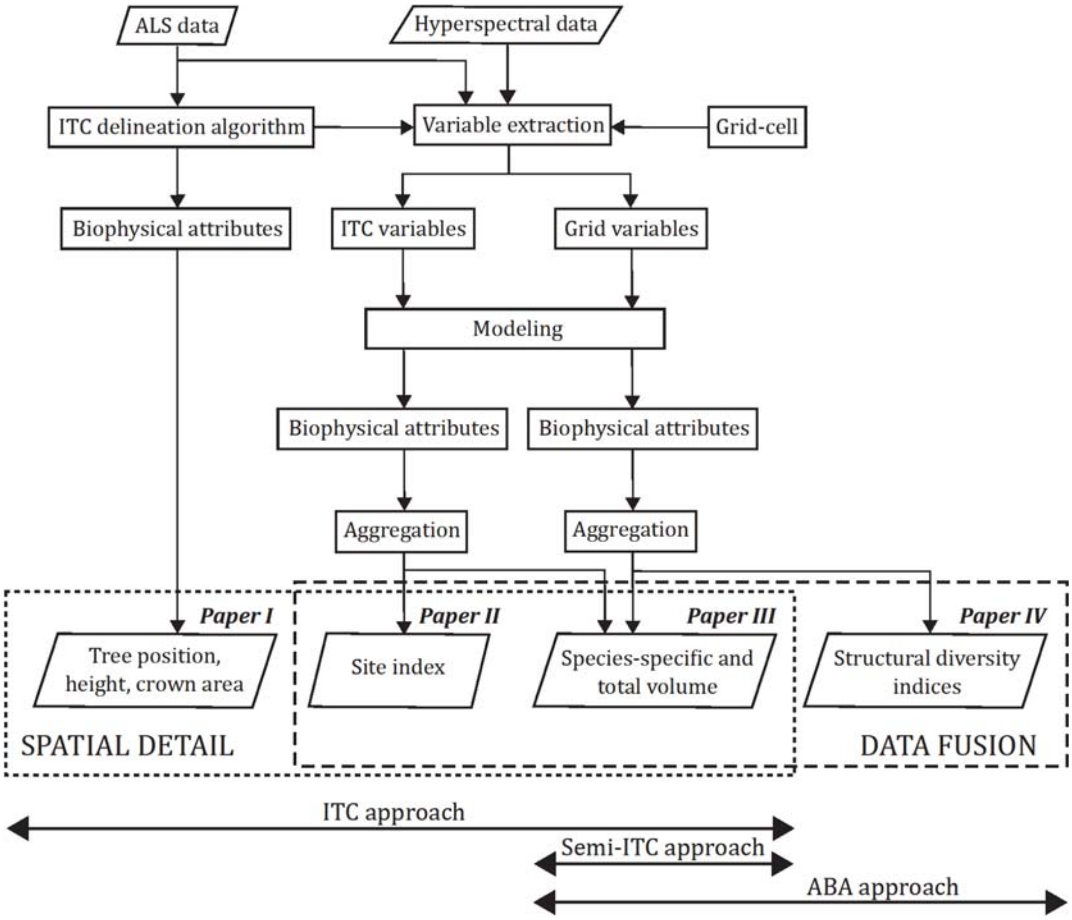

Figure 3: Flowchart explaining the connection between papers and objectives united in the current thesis.

2 Background

2.1 Airborne laser scanning (ALS) data

ALS is a method of adopting active laser sensor mounted on aircrafts which use the light detection and ranging (LiDAR) technology. LiDAR systems used in forestry mostly operate in the near-infrared region (e.g. 1064 nm), although some sensors also operate in the shortwave-infrared or green bands (e.g. Optech Titan sensor), for example to penetrate water and detect bottom features. LiDAR technology consists of an emitter and a receiver. The sensor emits many thousands of individual pulses of, i.e. near-infrared, light per second (Baltsavias, 1999). Each pulse penetrates partly into and possibly through the vegetation cover, and when the pulse reaches a target surface (e.g. branch, leave or ground), part of its energy is reflected back to the receiver. Most of the LiDAR devices used for ALS are time-of-flight LiDARs, and they measure the elapsed time between the emission of a pulse and the arrival of the reflection of that pulse at the sensor's receiver. Knowing the speed of the light and time of the pulse travel, the range is computed (Wehr and Lohr, 1999). From the range, the angle at which the pulse was "fired" (i.e. scan angle), and the absolute location of the LiDAR device the three dimensional (3D) coordinates (x, y, z) of the target object are computed. The position and orientation of the LiDAR device is continuously recorded along the flight path with a global positioning system (GPS) and an inertial measurement unit (IMU), which allow direct georeferencing. As the LiDAR device can measure for example 300,000 pulses per second, the resulting product is a densely-spaced cloud of highly accurate georeferenced elevation points often called ALS point cloud (Figure 1). In addition to the coordinates, information on the intensity of the backscattered pulse is usually recorded with the LiDAR system.

Each LiDAR system can have different specifications and settings related to the wavelength, power, pulse duration and repetition rate, beam size and divergence angle, the specifics of the scanning mechanism, and the information recorded for each pulse (Wehr and Lohr, 1999). Each emitted pulse can record the range and intensity of various objects along the pulse path and within the area illuminated by the light - footprint. According to the type of information recorded by the LiDAR system, two categories of sensors are distinguished, discrete return and full-waveform. The first can record up to five echoes, i.e. returns per pulse, which represent discrete objects in the path of the laser backscatter. The latter records the time-varying intensity of the returned pulse energy and captures the entire pulse trace. Both sensor types can operate with small (<1 m) or large (>10 m) footprint size. For example, forest inventory sample plot or a single tree can be characterized by a small footprint size, since such size of footprint allows high spatial resolution and can resolve the canopy structure up to a single tree. The vertical and horizontal accuracy can vary between 5-30 cm and 20-80 cm, respectively (Hohenthal et al., 2011). Data derived from a large footprint size are generally at a coarser resolution and can be used to characterize canopy structure of larger areas. The vertical and horizontal accuracy vary between 18-35 cm and 100-250 cm, respectively (Hohenthal et al., 2011).

The ALS technology is widely used in the surveying community to collect high precision 3D survey data. As LiDAR sensors provide a 3D representation of forest structure, it is possible to accurately assess forest biophysical attributes, such as height, basal area, volume, biomass, and canopy structure (Ferraz et al., 2016; Holmgren, 2004; Lee and Lucas, 2007; Lefsky et al., 1999; Næsset and Økland, 2002; Ozdemir and Donoghue, 2013; Varvia et al., 2016), and to provide high-resolution topographic maps (Jung et al., 2013; Tonolli et al., 2010; Valbuena et al., 2013). In addition, ALS data are used to estimate yields (Dash et al., 2015) and carbon stocks (Li et al., 2014; Stephens et al., 2012) of forest stands to ensure a sustainable supply of timber products, and to formulate silvicultural strategies (Coops, 2015; Pedersen et al., 2012). Moreover, ALS-based geometric reconstruction of forest stands also enables to manage wildland fire (Morsdorf et al., 2004), to monitor urban trees (Holopainen et al., 2013) and habitats (Hill and Hinsley, 2015), and to assess the assemblages of beetles (Müller and Brandl, 2009).

2.2 *Airborne hyperspectral data*

Hyperspectral remote sensing combines imaging and spectroscopy into a single system, also called imaging spectroscopy. Hyperspectral sensors are passive systems that collect and record through a detector the electromagnetic energy that is reflected or emitted by the surface of the objects. Hyperspectral imagery is created using an electro-optical sensor, which defines the range of angles through which incident light travel termed as "field of view". All objects within the field of view are imaged with the detector that records the spatial data and spectra of an object (i.e. radiance). The radiance is the amount of light the instrument detects and that is emitted by the object being observed.

Airborne hyperspectral sensors can be classified into four groups: whiskbroom (point scan), pushbroom (line scan), tunable filter (wavelength scan), and snapshot, and the first two are the most commonly used in remote sensing applications. Whiskbroom hyperspectral imagers are based on a single hyperspectral detector that collects the spectral signature of a single pixel at a time. The detector moves along a scanning line that is perpendicular to the flight line. The opposite is true for the pushbroom technology, also known as line scanning, where a series of many detectors, aligned perpendicularly to the flight line, scans the ground along a line parallel to the flight line. On the platforms, the IMU and GPS systems are used to correct the geometry of the data and relate each pixel in the output imagery to a location on the ground. Hyperspectral data used in this thesis were based on airborne platforms and the pushbroom spectral scanning concept.

Each hyperspectral image consists of pixels, with spatial information collected in the xy-plane, and a spectral information represented in the z-direction. The image spatial resolution is defined by the pixel size, and it could be smaller than 1 m when mounted on airborne platforms. For all the objects captured in the image, the spectral signatures are measured in a large number of narrow spectral bands from the visible to the shortwave infrared part of the spectrum. The number of bands can vary from several tens to hundreds of bands, with narrow bandwidth, usually between 5 to10 nm. The band width may be larger in the near infrared or shortwave infrared wavelength range. The greater is the number of bands, the higher is the level of spectral detail in the hyperspectral images, which gives better capability to see the unseen. Thus, each pixel contains a unique spectral signature, which can be used by the processing techniques to identify and characterize particular objects or materials within a scene. Different objects, for example different tree species, have different spectral signatures (Figure 4). The spectrum is a plot of wavelength versus radiance or reflectance. For example, the spectral signature of trees in the near infrared bands can be different due to species type, plant stress, and canopy state.

When the radiance is processed in order to compensate for the atmospheric effects and the solar illumination, reflectance can be obtained (Schaepman-Strub et al., 2006). In this context, the quality of the atmospheric correction algorithms directly impacts further data post-processing and exploitation. However, it was demonstrated that for certain applications the atmospheric correction process is not necessary and is not strictly required (Schaepman-Strub et al., 2006). Due to illumination effects, the time of acquisition is very important, and the ideal time interval is between 10:00 a.m. and 2:00 p.m. as this provides better illumination and a favorable angle of incidence, or sun angle (Borengaser et al., 2008).

The major advantage of the hyperspectral sensors is that their narrow bandwidths allow a high spectral resolution, which provides more detailed information on the spectral characteristics of the target respect to the wide bands used by the multispectral sensors (Dalponte et al., 2013). Additionally, hyperspectral data have been found to be more efficient in tree species classification than multispectral data (Dalponte et al., 2012; Ørka et al., 2013). The main disadvantages of hyperspectral data are that the processing of the information is more difficult and that the acquisition constraints are higher than with the multispectral data.

Many studies found that hyperspectral data are useful to provide information on vegetation types, tree and canopy phenology, physiology, foliar biochemistry content of forest canopies, and spectral signatures for selected tree species (Asner, 2008; Asner et al., 2017; Kokaly et al., 2009; Ustin et al., 2004).

In the forestry and ecology domains, hyperspectral data are powerful in tree species classification and plat traits prediction, which is needed by a wide variety of applications. These applications include forest inventories (van Aardt and Wynne, 2007), biodiversity and wildlife-habitat assessment and monitoring (Clawges et al., 2008; Shang and Chisholm, 2014), hazard and stress management (Fassnacht et al., 2014, 2012), monitoring of invasive species (Boschetti et al., 2007), wildlife habitat mapping (Santos et al., 2010), disturbances in the vitality of forests (Lausch et al., 2016, 2013), changes of plant communities and ecosystems (Asner et al., 2015), floodplain vegetation prediction (Geerling et al., 2007), and forest trait diversity mapping (Asner et al., 2017). Tree species information is as well as important to predict species-specific forest biophysical attributes (Kandare et al., 2017b; Ørka et al., 2013).

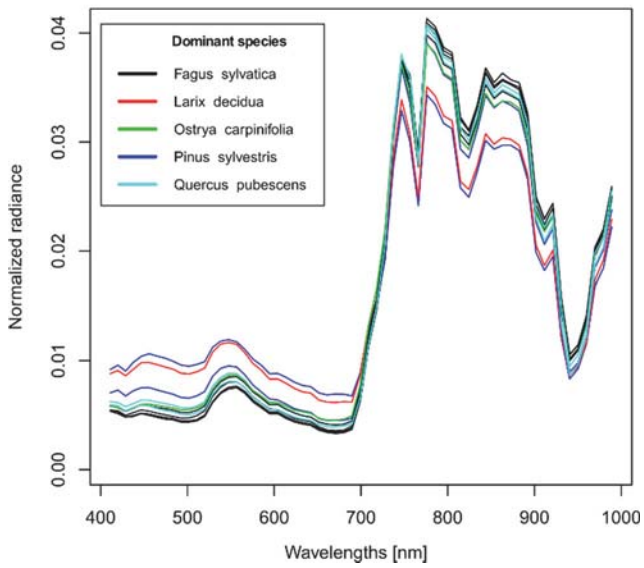

Figure 4: Example of spectral signatures of different tree species.

2.3 ITC approach and delineation algorithm

Individual trees are the smallest unit on which the forest management is carried out within the tree level forest inventory (Maltamo et al., 2014). The idea is to base the inventory on the characterization of individual trees in the area of interest. The first step of the tree level inventories is to detect and delineate individual tree crowns, also referred to as crown segments. For the delineation of tree crowns, ALS data were found superior to passive optical data as they are less affected by occlusions and shading (Voss and Sugumaran, 2008), and it is also possible to reach higher delineation and detection quality with ALS data (Dalponte et al., 2015b, 2014). For each delineated crown segment, the biophysical attributes, such as tree height, crown area, DBH, stem volume, and age, can be extracted or modelled (Ferraz et al., 2016; Kandare et al., 2016). When crown segments are co-registered with the hyperspectral data, hyperspectral variables can also be obtained as the aggregation of the digital value of the pixels within each crown segment as first order statistics (e.g. mean, variance, skewness, and kurtosis)(Kandare et al., 2017a). Moreover, forest attributes can be modelled by relating field observations with ALS and/or hyperspectral variables calculated for each crown segment. The most common point-based ALS variables computed for each crown segment based on height are: percentiles, mean, maximum, minimum, coefficient of variation, standard deviation, variance, skewness, and kurtosis (Breidenbach et al., 2010; Næsset and Økland, 2002; Ørka et al., 2013; Yu et al., 2010). In addition, crown projection area and crown density metrics computed as cumulative proportional densities for different height thresholds (Næsset and Økland, 2002; Yu et al., 2011). All these ALS variables can be calculated for the first, intermediates, and/or last returned LiDAR pulses. Some forest characteristics can be obtained without modelling. For instance, tree height and crown area can be directly extracted from each crown segment by maximum ALS point (z) and the projection of x and y coordinates of ALS points on horizontal plane, respectively (Kaartinen and Hyyppä, 2008; Morsdorf et al., 2004; Næsset and Økland, 2002; Yu et al., 2011, 2010). The obtained biophysical attributes of each crown segment can be further aggregated to any grid-cell size.

One of the first delineation algorithm was proposed by Hyyppä and Inkinen (1999). In the last two decades, numerous delineation algorithms were developed (Duncanson et al., 2014; Ene et al., 2012; Kandare et al., 2016; Persson et al., 2002; Reitberger et al., 2009; Solberg et al., 2006; Strîmbu and Strîmbu, 2015). Some of them are based on 2D canopy height model, 3D ALS points, or the combination of both. The evolution of such a great number of delineation algorithms emerged as there is no such method that would be applicable in different forest types (e.g. boreal, tropical, temperate deciduous forests) and conditions (e.g. structure, productive capacity, cover) governed by a variety of different management regimes (Kaartinen et al., 2012; Wang et al., 2016). Moreover, the performance of the delineation algorithm is quantitatively validated by different detection accuracy measures: omission error, commission error, detection rate, and accuracy index. The omission error is accounting for the number of field-observed trees that were not detected by the delineation algorithm (Equation 1). This kind of error occurs especially in dense forests, when trees grow close to each other and are consequently segmented as one crown segment. When a delineation algorithm detects a crown segment that is not matched with any field-observed trees, it leads to the commission error (Equation 2). This usually happens when tree crowns are big and the algorithm split one tree into two or more crown segments. The detection rate indicates the rate of correctly delineated field-observed trees (Equation 3). The accuracy index considers both omission and commission errors into a single metric (Equation 4).

$$Omission\ error = \frac{N_F - C_M}{N_F} 100\% \qquad \textit{Equation 1}$$

$$Commission\ error = \frac{C_{NM}}{N_F} 100\% \qquad \textit{Equation 2}$$

$$Detection\ rate = \frac{C_M}{N_F} 100\% \qquad \textit{Equation 3}$$

$$Accuracy\ indec = 100\% - (Omission\ error + Commission\ error) \qquad \textit{Equation 4}$$

In Equations 1-4, N_F is the actual number of field-observed trees, C_M is the number of correctly matched, and C_{NM} is the number of crown segments without a match with a field tree. To obtain C_M and C_{NM} values, a matching procedure is conducted, following various thresholds for permitted horizontal and/or vertical distance between field-observed trees and crown segments (Eysn et al., 2015; Wang et al., 2016).

2.4 Semi-ITC approach

The semi-ITC approach is equivalent to the ITC approach regarding the ITC delineation algorithm and the computation of the ALS and hyperspectral variables. They are distinguished by the matching procedure (Kandare et al., 2017a). In the common matching procedure of the ITC approach, the rule is that only one field tree can be matched with one crown segment, if not a field tree remains unmatched. Differently, in the semi-ITC approach more than one field tree can be matched with one crown segment (Breidenbach et al., 2010). Furthermore, all field trees must be matched with the closest crown segment. With such matching procedure, the omission and commission errors are substantially reduced in the following prediction models (Breidenbach et al., 2010; Kandare et al., 2017a). Subsequently, field measurements of biophysical attributes from accurately georeferenced sample plots are related to the remote sensing variables of crown segments taken from exactly the same area, and prediction models are developed. The predicted values of forest attributes are provided for trees within a sample plot area. Moreover, the prediction models can be exploited to predict the forest attributes of interest at any grid-cell size by aggregation of predicted attributes. According to the literature, the semi-ITC method has never been used in an application context and only a few studies exist (Breidenbach et al., 2010; Kandare et al., 2017a; Ørka et al., 2013; Rahlf et al., 2015).

2.5 ABA approach

In the majority of the forest management purposes assisted by ALS data, the area based approach (ABA) is used (Næsset et al., 2004). This approach was introduced by Næsset (2002). In the ABA, forest attributes are predicted for each element (e.g. grid cell) of a population with the size of each element being equal to the area of the sample plots. For each sample plot several remote sensing variables are extracted, for which predictive relationships with field-observed forest attributes are constructed. Furthermore, the prediction models can be utilized to predict the forest attributes of interest where the smallest grid-cell size is equal to the size of the sample plots. Typical ALS variables used in this approach are the height metrics (percentiles, mean, maximum, minimum, coefficient of variation, standard deviation, variance, skewness, and kurtosis) and the canopy density metrics (Næsset, 2004; Packalén et al., 2012). The canopy density variables can be calculated as the proportions of laser echoes above each defined height threshold in relation to the total number of echoes. All these variables can be computed for all echoes' categories. The hyperspectral variables can be computed as the average value of first order statistics for pixels within a grid-cell or sample plot (Kandare et al., 2017a). Additionally, variables can be computed from vegetation indices (Luo et al., 2017) or grey level co-occurrence matrices (e.g. contrast, energy, and correlation) (Meng et al., 2016; Packalén et al., 2012).

Currently, the ABA is the most used approach for operational forest inventories due to less demanding collection of the field data, and it can work quite well also at very low ALS point density (e.g. < 3 pulses m^{-2}).

2.6 Fusion of ALS and hyperspectral data

In order to fulfil the requirements for a comprehensive forest ecosystem characterization some complex forest characteristics cannot be accurately determined by one remote sensing system alone (Zhang, 2010). In such cases, the fusion of the complementary remote sensing data could offer a good solution to retrieve robust assessments. Due to accurate 3D measurements of forest structure and spectral measurements, specifically rich on information for biophysical and chemical canopy properties, obtained by ALS and airborne hyperspectral data, respectively, the fusion of both data systems has become very promising for evaluating forest characteristics (Fassnacht et al., 2016; Luo et al., 2017). Although, such fusion can be complicated due to the differences in the measured physical quantities (elevation vs radiance), geometry of data acquisition (3D points vs 2D image) and sources of illumination (laser vs solar radiation). Data fusion, sometimes also called data combination or integration, can be employed by 1) empirical or statistical, 2) physical, or 3) hybrid approaches (Torabzadeh et al., 2014). The most straightforward is the statistical approach, which will be the main focus in the current thesis, based on predictive models e.g. generalized linear models, ordinary least squares, k-nearest neighbor algorithm, support vector machines, etc.

One of the first attempts exploring the fusion of ALS and hyperspectral data in forestry domain was carried out in 2004 (Gillespie et al., 2004), followed by other studies assessing and producing land cover maps (Asner et al., 2008; Dalponte et al., 2012; Hill and Thomson, 2005; Koetz et al., 2008), above ground biomass (Anderson et al., 2008; Clark et al., 2011; Dalponte et al., 2015b; Luo et al., 2017; Swatantran et al., 2011; Vaglio Laurin et al., 2014), volume (Kandare et al., 2017a), species composition (Dalponte et al., 2008; Jones et al., 2010; Koetz et al., 2008; Richter et al., 2016), etc. mostly in tropical and temperate forests. These studies were carried out mostly in tropical and temperate forests, and there is a need to test data fusion over a wider range of forest cover and types. Among this studies, only a few were conducted on temperate forests in the Alps and boreal forest types (Dalponte et al., 2014, 2012; Ørka et al., 2013).

The statistical data fusion approaches used in this thesis could be categorized into 1) product-level, where separate processing chains for ALS and hyperspectral data are conducted to compute biophysical attributes, i.e. tree species with hyperspectral and volume by ALS, and then the attributes are fused to provide species-specific volume; and 2) variable-level, where both ALS and hyperspectral variables are combined into empirical models to predict biophysical attributes, i.e. species-specific volume. The product-level fusion is more common for the ITC approach and the variable-level fusion for semi-ITC and ABA approaches. ITC and semi-ITC approaches allow to obtain accurate biophysical attributes at tree level thanks to the delineation algorithm. When ALS and hyperspectral data are co-registered, both ALS and spectral variables are computed for each crown segment. For the ITC approach, spectral information per crown enables to preform tree species classification resulting in high accuracies (Dalponte et al., 2013, 2008). Fusing species information with ALS-derived forest attributes per each crown segment, results can be obtained in species-specific forest attributes such as volume, basal area, and stem density, which are valuable information for forest managers. With the semi-ITC approach, the classification of tree species per crown is not possible because crown segments can contain one or more tree species. Thus with semi-ITC and ABA approaches only species proportions within a segment/grid can be predicted.

2.7 Forest characteristics investigated in this thesis

Based on biophysical attributes, such as tree age, species, position, DBH, and height, many forest characteristics, such as site index or structural diversity measured can be obtained. Site index is a very common quantitative measure and widely accepted method of forest site productivity defined as expected height of the trees at a given base age (e.g. 70 years) for certain tree species in area of interest (Skovsgaard and Vanclay, 2008). In order to ensure a sustainable supply of timber products and to formulate silvicultural strategies the reliable site index estimates are important. Forest structural diversity can be described by variability in spatial arrangement of trees, tree dimensions, and mingling of different tree species (Aguirre et al., 2003; McElhinny et al., 2005; Pommerening, 2002). These characteristics, called structural diversity measures, can be quantified through, e.g. diameter differentiation index, Gini coefficient of basal area, uniform angle index, mean nearest neighbors, Shannon's index, species mingling index, etc. (Meng et al., 2016; Neumann and Starlinger, 2001; Pommerening, 2006). Structural diversity measures are crucial in order to gain a better understanding of forest ecosystems as they express the sustainability of management practices for economic as well as environmental purposes. Moreover, information of structural diversity is also important to describe forest health, to model animal and forest plant species behavior, and to predict forest fire behaviors (Lausch et al., 2016; Martinuzzi et al., 2009; Morsdorf et al., 2004).

3 Material

3.1 Study areas

In the current thesis, two study areas were used: 1) a temperate forest in the municipality of Pellizzano in the Italian Alps (46°17′22′′N, 10°46′05′′E, 900–2220 m above sea level) (Figure 5);

and 2) a boreal forest in the Våler municipality in south-eastern Norway (59°30′N 10°55′E, 70–120 m above sea level) (Figure 6).

3.1.1 Pellizzano

The Pellizzano study area extends on 3200 ha. The forest is dominated by Norway spruce (*Picea abies* (L.) Karst.), with the presence of other coniferous species (e.g., larch (*Larix decidua* Mill.), silver fir (*Abies alba* Mill.)) and broadleaves species (e.g., rowan (*Sorbus aucuparia* L.), common hazel (*Corylus avellana* L.), silver birch (*Betula pendula* Roth), and sycamore maple (*Acer pseudoplatanus* L.)). At higher altitudes, the forest is sparse, whereas at lower altitudes, the forest structure is more complex, varying from a one-to multi-layer forest with patches of mixed and homogeneous tree species composition. The area has been managed since 1950 with silvicultural plans implemented every 10 years. Selective logging is done with the help of cableway focusing on the productive forest area, especially Norway spruce, and trees are harvested according to their stem diameter.

3.1.2 Våler

The Våler study area cover 853 ha. The dominant species are Norway spruce (*Picea abies* (L.) Karst.) and Scots pine (*Pinus sylvestris* L.). Younger stands have large proportions of deciduous species dominated by birch trees (*Betula pubescens* Ehrh.). The active forest management in the forest area is directed towards the timber production with clear-cuts and shelterwood cutting applied at the end of the rotation depending on the site fertility. For the former harvest method, the regeneration is achieved by plantation, and for the latter by natural regeneration after selective logging.

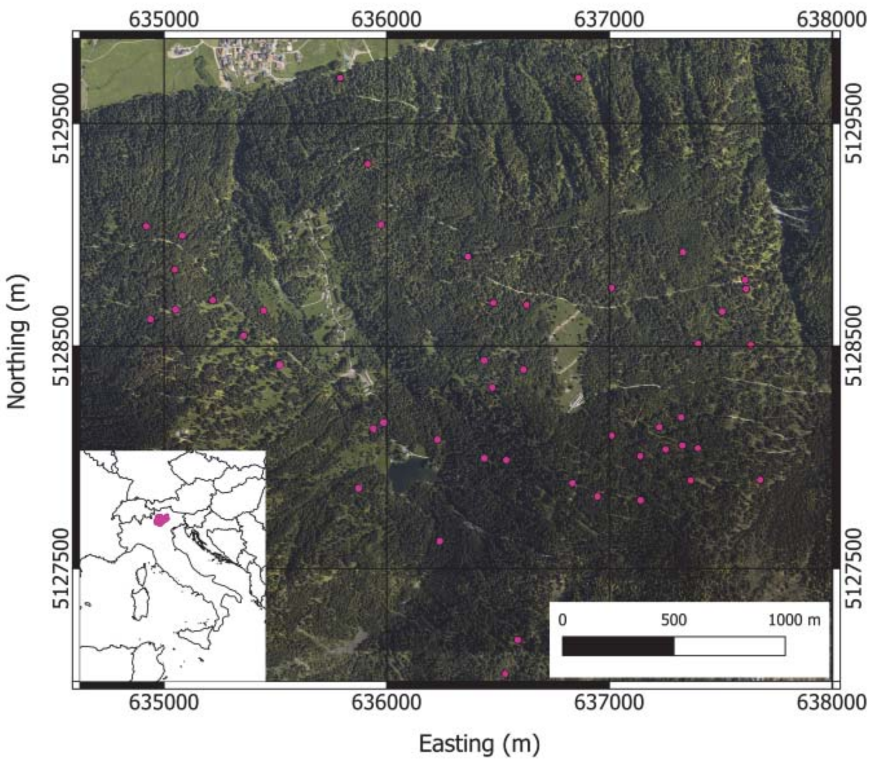

Figure 5: Map of the Pellizzano study area. The pink dots are indicating the field plots.

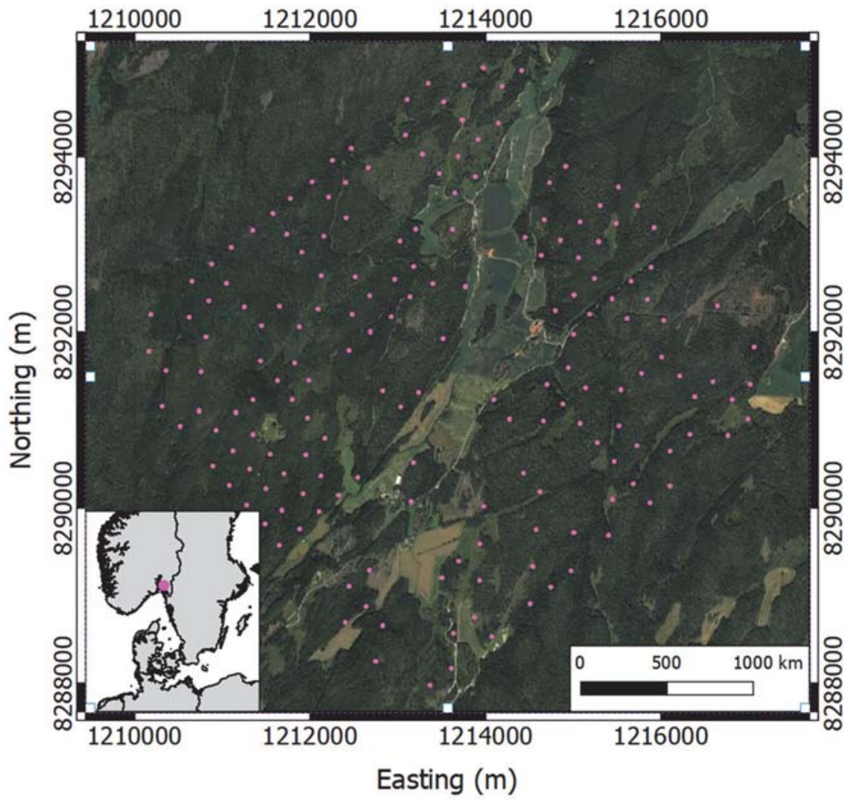

Figure 6: Map of the Våler study area. The pink dots are indicating the field plots.

3.2 Field data

3.2.1 Pellizzano

During the summers of 2013 and 2015, 47 circular sample plots were surveyed. The size of the sample plots was 700 m^2. The center location of each plot was determined with a GPS and global navigation satellite system (GLONASS) measurements, resulting in a positional error of less than 1 m. For all trees within the sample plot, the location was recorded as a polar coordinates to the center of the plot (azimuth and range). In addition, DBH along two orthogonal directions and tree species were recorded. Tree height on two-thirds of randomly selected trees was measured using a Vertex III hypsometer. Tree heights of the remaining trees were predicted with allometric equations (Scrinzi et al., 2010). Dead or damaged trees were excluded. The tree species observed for the 1888 trees were: 72.9% Norway spruce, 7.9% rowan, 7.1% larch, 1.7% silver birch, 1.3% silver fir, 1.3% common hazel, 1.2% sycamore maple, and the rest were other minority broadleaves.

3.2.2 Våler

In 2010, 153 systematically distributed circular sample plots were inventoried. The size of each plot was 400 m^2. For all trees inside the plots with DBH above 4 cm the tree position, tree species, and DBH were recorded. Tree height was measured only on selected sample trees, approximately for 10 trees per plot. The polar tree coordinates were established by using measurements of distance and angle from the plot center. These measurements were carried out with a tape measure and a compass with a sight. The plot center was measured using differential GPS and GLONASS receiver. Out of 9414 recorded trees, 52% were spruce, 25% were pine, and 23% were broadleaves.

In July 2013, 96 of the forest inventory plots dominated either by spruce or pine were revisited to measure data for site index determination. Out of 384 recorded trees, 58% were spruce and 42% were pine trees. In each plot, the four largest trees according to DBH of the dominant species were selected as sample trees, which corresponds as closely as possible to the definition of the dominant trees, i.e., the 100 largest trees per ha (Rennolls, 1978), given the limited plot size of 400 m^2. For each sample tree, the position, height, and DBH were recorded. For further age analyses, core samples of two dominant trees per plot were taken at 1.3 m height. In the laboratory, the age was obtained by counting growth rings on the core samples. The ring widths were measured manually with the LINTABTM 6 tree-ring measurement station and the TSAP-WinTM software for tree-ring measurement.

3.3 ALS and hyperspectral data

3.3.1 Pellizzano

ALS data were acquired between 7th and 9th September, 2012 with a Riegl LMS-Q680i laser scanner. The system, mounted on a Multi Mission Aircraft, was optimized to measure canopy structure with a flying speed of about 51 m s^{-2} at an altitude of 660 m above ground level. The pulse repetition frequency was 400 kHz with a 60° field of view and the overlap for each stripe was at least 30%. The result of the scanning was an ALS point cloud (x, y, z) with a mean point density of 48 pulses m^{-1} for the first returns. The scanner recorded up to five returns for each laser pulse. The data vendor generated a digital terrain model (DTM) with TerraScan software with a spatial resolution of 0.5 m. Furthermore, ALS point cloud was normalized to obtain a canopy height above ground by subtracting the DTM elevations from the z values of the ALS pulses.

Hyperspectral data were acquired on 13th June 2013 with an AISA Eagle II sensor with a spatial resolution of 1 m. Twenty-one images were acquired between 12:00 a.m. and 1:12 p.m. and mosaicked in order to create a uniform image. The minimum overlap among the images was 20%. Each image was characterized by 65 spectral bands acquired between 403.1 nm and 995.3 nm with a spectral resolution of 9 nm. Non-vegetated areas were removed by filtering out pixels with a normalized difference vegetation index (NDVI) below 0.5. To reduce minor differences in reflectance occurring between different images, the value of each pixel was normalized dividing it by the sum of the (original) values of the same pixel along all the bands (Yu et al., 1999).

3.3.2 Våler

ALS and airborne hyperspectral data were simultaneously acquired over the study area on 9th September 2011. The flying altitude was 1500 m above ground level. Twenty-one flight lines were flown between 10:48 a.m. and 2:22 p.m., having sun zenith angle between 59° and 61°. ALS data were acquired using the Leica ALS70 system with a pulse repetition frequency of 180 kHz. The system recorded up to five returns per pulse and the average pulse density was 2.4 pulses m^{-2}.

Hyperspectral data were acquired using the HySpex VNIR-1600 sensor with spatial resolution of 0.5 m. The images consisted of 80 bands between 410 nm and 990 nm with 7.2 nm spectral resolution. All the hyperspectral images were acquired in non-nadir conditions regarding the field plots. Hyperspectral data were orthorectified using a DTM derived from ALS data by the data vendor. To minimize co-registration problems the vendor also applied a transformation based on tree top detection in the two datasets. In the pre-processing, the hyperspectral images were atmospherically corrected using the QUAC algorithm (Bernstein et al., 2005). Afterwards, the value of each pixel was normalized with respect to the sum of the values of the same pixel in all the bands to reduce a minor difference in reflectance occurring between the different images (Yu et al., 1999).

4 Methods

In this thesis, the fusion is employed by a statistic approach, which is based on predictive models, such as generalized linear models, k-nearest neighbor algorithm, support vector machines (SVM) classifier etc. The statistic approach was investigated on product and variable-level, using exploratory data analysis, parametric and non-parametric machine learning algorithms for modeling and different statistical tests (Table 1). The detection accuracy of the delineation algorithm was evaluated with omission error (OE), commission error (CE), and accuracy index (AI). The model accuracy for the forest characteristics was evaluated in terms of the root mean square error (RMSE) and the coefficient of determination (r^2) computed as the square value of Pearson correlation coefficient. The systematic error was assessed with the mean differences (MD). For the ITC approach, the tree species classification accuracy was validated with the overall accuracy (OA), kappa coefficient (KA), and the producer's and user's accuracies derived from the confusion matrix. The reliability of the predicted forest characteristics was tested by means of the cross-validation technique.

Table 1: Summary of exploratory data analysis, machine learning algorithms for modeling, test statistics, and accuracy measures applied in Papers I, II, III, and IV.

	Paper I	**Paper II**	**Paper III**	**Paper IV**
Exploratory data analysis	Parameters tuning and sensitivity analysis	/	/	/
Machine learning algorithms	K-means clustering	Linear regression, Poisson regression, SVM classification	Linear and non-linear regression, k-nearest neighbors, SVM classification	Partial least square regression
Test statistics	Two-sided Mann-Whitney-Wilcoxon test	/	Wilcoxon signed rank test, Friedman test, Conover post-hoc analysis	Permutation test
Accuracy assessment	OE, CE, AI, RMSE, MD, r^2	OE, CE, OA, KA, producer's accuracy, RMSE, MD, standard deviation of the differences, r^2	OE, CE, OA, KA, producer's and user's accuracies, RMSE, MD, r^2	RMSE, MD, q^2

The ITC delineating algorithm was based on a K-means clustering applied on horizontal slices followed by vertical merging based on overlapping among clusters. In addition, the effects of different forest structures (characterized by mean DBH, number of stems per hectare, mean nearest neighbor distance, and Gini coefficient of basal area) and point cloud densities (50, 30, 20, 10, 6 and 4 pulses m^{-2}) on the ITC delineation algorithm were analysed in terms of omission and commission errors. To test if the differences among accuracies obtained with different point cloud densities and original data were significant, a two-sided Mann-Whitney-Wilcoxon test was carried out. For each crown segment, biophysical attributes (tree height, crown area, and crown position) were extracted at the ITC level and aggregated at the plot level (Paper I).

The same ITC delineation algorithm was applied in the study of Paper II. Moreover, once the crown segments were delineated, they were co-registered with the hyperspectral data in order to obtain ALS and hyperspectral variables for each delineated crown segment. These variables were used to predict forest attributes at the ITC level. Tree species were predicted with SVM classifier and used to predict age per species with Poisson regression using ALS and hyperspectral variables, while stem height and DBH were predicted with ALS variables fitting species-specific linear models. The models were validated using a 10-fold cross validation approach. Subsequently, these biophysical attributes were used to compute dominant height, species, and age for each sample plot in order to determine the site index at grid level (Paper II).

The species-specific volume was predicted with ITC, semi-ITC, and ABA approaches. For the ITC approach, hyperspectral variables were used to predict tree species with SVM classifier, and ALS variables to predict DBH with non-linear regression models. Knowing the predicted species and DBH, the species-specific volumes were computed based on allometric models. For the semi-ITC and ABA approaches, the statistical relationships between the ALS and hyperspectral variables, and the field-observed species-specific volumes were constructed based on multivariate k most similar neighbor (MSN) method. The ALS and hyperspectral variables were calculated for each crown segment in the semi-ITC approach and for each sample plot in ABA. The species-specific volumes for ITC and semi-ITC were aggregated at the same grid size as ABA in order to compare and evaluate the performance of each approach. Wilcoxon signed rank test was performed to test the significance of the differences between the observed and predicted volumes for each inventory approach. The Friedman test was applied to check the significance of the differences in the distribution of the differences between the observed and predicted species-specific volumes among sample plots for the three inventory approaches. For validating species-specific volumes, leave-one-out (LOO) cross-validation procedure was applied (Paper III).

The ALS (height and density matrices) and hyperspectral variables (1st and 2nd order image statistics) were computed for each sample plot and used in partial least square (PLS) regression models in order to predict six forest structural diversity measures. We checked if the encoded information may be useful for prediction purposes when considering ALS and hyperspectral variables, either alone or fused. The optimal number of latent variables was selected by minimizing the RMSE of predictions based on a 5-fold cross-validation. The number of ALS and hyperspectral variables was balanced using the correlation threshold, thus, equally weighing the impacts of both kind of variables on the PLS model. A permutation test was applied to test each model's reliability. The model accuracy and systematic error were compared using ALS and hyperspectral data, separately or fused (Paper VI).

5 Major findings

5.1 Quantification of influence of forest structure and ALS point cloud density on established ITC delineation algorithm (Paper I)

With the field measurements and a well-established reference delineation method, the performance of the developed ITC delineation method based on ALS data was evaluated in terms of detection accuracy and tree attributes estimation. Both methods reached similar detection accuracies and both were effective in tree attributes estimation. Forest structure characterized by stem density, distribution of trees, number of stems per hectare, and the evenness expressed by Gini coefficient of basal area, had significant influence on the detection accuracy in terms of omission and commission errors. The omission error was lower (in range of 25%–60%) in plots with a homogeneous forest structure and tree species, and higher (in range of 60%–85%) in plots with a heterogeneous forest structure and tree species. In addition, the forest structure only had a slight effect on the commission error as it was similar for all plots. The point density analysis showed that the detection accuracy, in terms of accuracy index, marginally increased for the point densities from 6 to 50 pulses m^{-2} applying Mann-Whitney-Wilcoxon test. However, the accuracy index of the ITC delineation algorithm was the highest with the original point cloud density at 60 pulses m^{-2} and significantly different from the other point cloud densities.

5.2 Improvement of site index maps using ITC approach together with fused ALS and hyperspectral data (Paper II)

Plot level-derived biophysical attributes via ITC approach using ALS and hyperspectral data provided a reliable input for the determination of site index. ALS variables obtained for each crown segment were important for the height and DBH modeling, while the fused ALS and hyperspectral variables were important for tree species and age modeling. The selection of the dominant crown segments derived from ITC delineation algorithm from which the inputs for the site index were computed, did not affect the accuracy of the predicted site index. The prediction accuracies of dominant height and species were high (RMSE = 1.12 m and kappa accuracy = 0.85) in contrast to errors related to age (RMSE = 34.01 years). The RMSE for site indices was 4.30 m when all biophysical attributes (dominant height, tree species, and age) were predicted from the remote sensing data and 1.18 m when only the age was taken from the field measurements. Age prediction based on remotely sensed data is still a challenging task, especially in mixed age stands. The site index determination based on ITC delineation at the variable-level fusion was stable and efficient for the site index determination.

5.3 Evaluation of the performance of three remotely sensed-based forest inventory approaches to assess how different spatial details influenced the predictions of species-specific volume using fused ALS and hyperspectral data (Paper III)

Three remotely sensed-based forest inventory approaches were compared (ITC, semi-ITC and ABA approach). The fusion for the first approach was conducted on the product-level, and for the others at the variable-level. The hyperspectral data were important in the ITC approach for the classification of tree species, and ALS data for the DBH and height prediction which together allowed the predictions of species-specific models. For the semi-ITC and ABA approaches, ALS and hyperspectral variables were combined into *k*-mean nearest neighbor models. The ITC approach performed better according to relative RMSE for the volumes of minority species but in general resulted in larger systematic errors (relative mean differences of the mean) compared to the semi-ITC and ABA approaches. The ABA approach resulted in relatively high accuracies and small systematic errors for the dominant species and vice versa for the minority species. For majority species, the semi-ITC performed slightly better compared to the ABA, resulting in higher accuracies and smaller systematic errors. The total volume of the ITC, semi-ITC, and ABA resulted in relative RMSEs of 25.31%, 17.41%, and 30.95% of the mean and relative mean differences of 21.59%, 0.27%, and 2.69% of the mean, respectively. The results indicated that the semi-ITC outperformed the two other inventory approaches, considering the greatest balance between accuracies and the systematic errors. The Friedman's test demonstrated that the pairs of the inventory approaches (ITC vs. semi-ITC, ITC vs. ABA, semi-ITC vs. ABA) were significantly different ($p \leq 0.05$) from each other for the total and species-specific volumes, except for the pair of semi-ITC vs ABA, where the Norway spruce and larch volumes were not statistically significant. For the ITC approach, hyperspectral variables were important for tree species identification, while ALS data were important for ITC delineation in order to extract crown segment height and crown area for predicting DBH. Both species and DBH, were considered as inputs for volume prediction. In the semi-ITC and ABA approaches, the ALS and hyperspectral variables were both important for volume modeling.

5.4 Investigate the benefits of ALS and hyperspectral data, separately and fused, to predict forest structural measures (Paper IV)

Six types of measures of forest structural diversity that describe the variability of tree sizes (Gini coefficient of basal area and diameter differentiation index), the spatial distribution of tree positions (mean nearest neighbor distance and uniform angle index), and the tree species diversity (Shannon's index and species mingling index) were considered. The forest structural diversity measures were predicted with ALS and hyperspectral data, alone and combined, where the data fusion was conducted at variable-level. None of the structural diversity measures based on hyperspectral data passed the permutation test meaning that the predictions were not different from a random prediction. The uniform angle index was the only one that was not predictable with any remote sensing data combination. Fused data improved the prediction performances of the diameter differentiation index only, when obtained as a combination of ALS and 2nd order image statistics on hyperspectral data. Compared to predictions based on ALS data, the predictions based on fused data reached higher relative RMSE for 5 percentage points and variance explained by model was higher for 28 percentage points. The fusion of ALS and hyperspectral data did not improve any other structural diversity measures, but produced accuracy levels comparable to the structural diversity measures derived from ALS data alone. In this experiment, ALS data showed the best predictions for the majority of the structural diversity measures taken into account.

6 Discussion

6.1 Fusion of ALS and hyperspectral data (Papers II, III, IV)

ALS and hyperspectral data were fused to provide species information, total and species-specific volume, height, DBH, age, site index, and structural diversity measures at different fusion levels. In particular, the fusion in Papers II and III was conducted at product-level, while in Papers II, III, and IV at variable-level (see Table 2). In the same order, the aforementioned forest characteristics will be discussed.

Tree species are characterized by different plant chemical and physical properties, which results in differing levels of reflectance (amplitude). Such differences significantly affect the reflectance spectrum shape (Fassnacht et al., 2016). These differences in reflectance from the visible to the shortwave infrared part of the spectrum are therefore the main drivers to discriminate species. Moreover, tree species also have different architecture of crowns (e.g. conical, rounded), branching, and foliage (Coops et al., 2007). Thus, the hyperspectral and ALS data can be considered the most promising combination for discriminating tree species and to outperform other data fusions, e.g. fusion of ALS and multispectral data (Dalponte et al., 2012; Ørka et al., 2013). In Paper II, such fusion was proved to be suitable in distinguishing tree species, especially for spectrally similar tree species. Similar was confirmed in the study of Dalponte et al. (2012). The classification accuracy was higher for the dominant species as they were more representative in samples compared to the minority species. This was also showed by Ørka et al. (2013). The species accuracy obtained in Paper II, was in line with the study of Dalponte et al. (2015a) conducted on the same study area. Moreover, the fusion of ALS and hyperspectral data was shown as a powerful basis for the discrimination of tree species also in other studies conducted on different study areas (Alonzo et al., 2014; Dalponte et al., 2014).

Using different inventory approaches to characterize the species composition was demonstrated with the combined use of ALS and hyperspectral data, and higher accuracies were achieved compared to other data fusions (Ørka et al., 2013). Moreover, many methods have been proposed for fusing ALS data with aerial photographs or airborne multispectral images (Breidenbach et al., 2010; Packalén and Maltamo, 2006; Vauhkonen et al., 2012) in order to predict species-specific volumes. According to the existing literature, in Paper III, the first attempt to fuse the ALS and hyperspectral data were investigated in order to provide species-specific volumes with three different inventory approaches. With the ITC approach, stem volume was predicted based on ALS data, and the species were classified based on hyperspectral data. Both coupled together enable to provide species-specific volume representing product-level fusion. In contrast, in the semi-ITC and ABA approaches, both ALS and hyperspectral variables were used for modeling total and species-specific volumes, and the fusion was conducted at a variable-level. The fusion of such complementary data at product- and variable-level provided the predictions with high accuracies. The results obtained in Paper III were in line with the study of Breidenbach et al. (2010) but we have to consider that both studies were applied to different forest types.

In Paper II, the fusion at the product-level was found important for the species-specific models of height and DBH. The age was modeled by fusing data on variable-level. Both ALS and hyperspectral variables were found important. In addition, the site index was determined by applying product-level fusion which was based on the abovementioned forest characteristics, and the results showed high potential to improve existing site index maps in an objective and automatic way. The fusion of ALS and hyperspectral data was found powerful to predict age, which was overpredicted in younger (< 60 years) and underpredicted in older (> 60 years) stands. The reasons of the importance of the fusion of ALS and hyperspectral data is two sided. First, with the aging, the canopy structure (Ishii and McDowell, 2002), plant chemical properties, and the leaf morphology (Roberts et al., 1997) are changing. Thus, changes in reflectance are measured by hyperspectral sensors. Dye et al. (2011) demonstrated that the hyperspectral data were suitable to predict age in young stands. Furthermore, the better the site productivity is and the higher the tree age is, the higher the tree can grow. Thus, it was demonstrated that ALS data can provide good age predictability (Racine et al., 2014). However, such relationship between ALS heights and age is usually strong in stands with smaller age variability or in even-aged stands. In the study area used in Paper II, the stands were mixed-age and the age-structure relationship in such stands is more ambiguous, since the strength of the relationship becomes asymptotic with aging. These was also confirmed by Ung et al. (2001) and Sharma et al. (2011). However, the accuracy of age predictions vary considerably between different studies, using only ALS or spectral data, and it seems to be strongly effected by forest management strategies, and forest structure and type (M. Maltamo et al., 2009; Niemann, 1995; Pretzsch, 2009; Racine et al., 2014).

In Paper IV, structural diversity measures describing tree size variation, spatial pattern of trees, and tree species diversity were predicted by ALS and hyperspectral data alone and both together fused at variable-level. According to the existing literature in relation to the forest structural diversity of biophysical attributes, the fusion of ALS and hyperspectral data was mostly explored for the estimation of the stem density and above ground biomass (Anderson et al., 2008; Latifi et al., 2012; Luo et al., 2017; Vaglio Laurin et al., 2014) and less for the structural diversity measures explored in Paper IV. The ALS variables provided the most effective information amongst the entire data source combinations, while the hyperspectral variables contributed only slightly to describe the variation beyond those explained by ALS. Similar was also highlighted by Anderson et al. (2008). Thus, data fusion generally did not contribute to the accuracy increase for structural diversity measures accounted in this study. Image texture refers to the spatial variation and arrangement of the pixels of which any image is composed. It could be that the distribution of trees and the tree species were similar among the sample plots, therefore hyperspectral variables did not make high contribution to the fused models. In many studies, the variables calculated from grey level co-occurrence matrix, which was derived from spectral images, were demonstrated as good variables in distinguishing spatial pattern in remote sensing imagery analysis, and they were mostly used for classification purposes (Franklin et al., 2001; Murray et al., 2010; Ouma et al., 2008) and less for modelling purposes (Gallardo-Cruz et al., 2012; Meng et al., 2016). To explain why fusion in Paper IV did not increase the accuracy of structural diversity measures, more research should be carried out in similar forest conditions, especially for modeling purposes.

From the processing point of view, the disadvantage of data fusion is that ALS and hyperspectral data require the co-registration of datasets, and any uncertainty at this stage could influence the accuracy of the final products (Torabzadeh et al., 2014). The advantage of such data fusion, when both sensors are combined on the same platform, is higher geometric accuracy for data fusion and highly compatible datasets, also proved for similar data fusions (St-Onge et al., 2008). In addition, when both sensors are mounted on a platform of the same mission, the cost is reduced. For mapping purposes, Jones et al. (2010) proved that ALS and hyperspectral data fusion was superior to aerial photograph interpretation in terms of accuracy and cost.

Considering the achieved accuracies in Papers II, III, and IV it can be seen that in most cases fused data obtain higher accuracies than ALS and hyperspectral data only.

Table 2: Fusion levels of predicted forest characteristics with ALS and hyperspectral data in Papers II, III, and IV.

	Paper II	**Paper III**	**Paper IV**
Product level	Height, DBH, Site index	Species-specific volume with ITC approach	/
Variables level	Tree species and age	Total and species-specific volume with semi-ITC and ABA approaches	Structural diversity measures

6.2 *Exploring different spatial scales in the prediction of forest characteristics (Papers I, II, III)*

The extraction and prediction of different forest characteristics (species information, age, total volume, species-specific volume, and structural diversity measures) at different spatial scales were investigated in Papers I, II, and III (see Table 3). With the ITC approach, all papers produced information with the highest spatial scale, the tree. Papers II and III provided information on the grid-cell scale using the ABA, while Paper II also considered the tree group scale using the semi-ITC. First, the ITC delineation algorithm and the point density is discussed, continued with the forest characteristics obtained with the ITC, semi-ITC, and ABA approaches.

Low point density ALS data provide limited possibilities to detect and delineate co-dominant and subordinate trees, i.e., the intermediate and suppressed trees. In this regard, ALS point cloud with density above 5 pulses per m^{-2} (Peuhkurinen et al., 2011) already allows development of delineation methods to better distinguish individual tree crowns. In many studies, it was assumed that the higher the point density, the better the detection and delineation of trees. This was shown to be particularly true in structurally complex and dense forests (Wang et al., 2016). In a few studies (Kaartinen et al., 2012; Wang et al., 2016; Yao et al., 2014), different point densities were tested, up to 8 and 20 pulses per m^{-2}. Kaartinen et al. (2012) and Yao et al. (2014) reported that there were no significant improvements in performances of the ITC delineation algorithms, at least for those datasets with a point density larger than 10 pulses per m^{-2}. Additionally, in both studies, the ITC delineation algorithms were mostly developed on 2D canopy height models. Thus, in such 2D delineation methods after a certain point density the information seemed to be saturated and the detection accuracy could not improve (Wang et al., 2016). With a different perspective, Wang et al. (2016) also considered delineation algorithms based on 3D ALS points and reported that such algorithms performed better with higher densities. However, the range of point densities considered in the abovementioned studies is too small to make any conclusions. One of the objectives in Paper I was to test if a high point density can improve the detection and delineation accuracy of the developed delineation algorithm based on 3D ALS points. This study was the first to evaluate point densities above 20 pulses considering point densities up to 60 pulses per m^{-2}. It was demonstrated that the detection accuracy increased with higher point densities, but it achieved marginal improvements when the point density expanded from 10 to 50 pulses per m^{-2}. This is in line with earlier research that have found that the detection accuracy did not change between 10 and 20 pulses per m^{-2}. However, with 60 pulses per m^{-2} the detection accuracy was significantly different compared to other point densities. Thus, a 3D delineation algorithm seems to be able to provide higher spatial detail using the high point density data. The optimal point density most probably depends on tree size, structure, and stand density of the forest. In Paper I, it was found that the detection accuracy was higher in more sparse and single layered forest. Thus, to detect the dominant trees the lower point densities could be used. This is in line with the suggestions of Wang et al. (2016) indicating that ALS data with point density between 2 to 5 pulses m^{-2} may already provide satisfactory results for the applications where the main focus is to obtain characteristics of dominant trees.

High point density could also affect the prediction accuracy of the forest characteristics related to the detected crown segments. Kaartinen et al. (2012) found out that the use of different point densities marginally improved the accuracy of the extracted tree heights, tree positions, and crown areas. Unfortunately, there are no studies that tested such effect on higher point densities. In addition, most studies were conducted on point densities below 8 pulses m^{-2} and were carried out at plot level (Manuri et al., 2017; Ruiz et al., 2014; Tesfamichael et al., 2010). In Paper I, attributes extracted from a 3D and a 2D algorithms were compared, and it emerged that they were quite similar between the algorithms. Moreover, the 2D method provided better estimates for the crown area.

The ITC and semi-ITC approaches can provide detailed forest characteristics, such as age, DBH, species, volume, etc. for each crown segment (Breidenbach et al., 2010; M Maltamo et al., 2009; Yu et al., 2010). However, the accuracy of such characteristics depends on the success of the ITC delineation algorithm and its calibration (Kandare et al., 2016; Latifi et al., 2015; Yu et al., 2010). Although the delineation algorithm was applied in Paper II and III, the results are hardly comparable at the tree level, because the characteristics were further aggregated at grid-level. In particular, in Paper II, only the four largest crown segments per plot were used for the calculation of forest characteristics at grid-level (dominant height, species, age, and site index) while in Paper III all delineated crown segments were used. The biggest advantages of the ITC and semi-ITC approaches are that they allow to obtain predictions at the minimum possible scale in a forest, such as a crown segment, and allow better localization of forest characteristic due to the known tree positions (Paper II, III). Indeed, in Paper II it was demonstrated that through the ITC approach it was possible to obtain site index results at an accuracy similar to the existing site index maps in Norway. We have to keep in mind that site index on the existing maps has one value for each stand while with the ITC approach we are able to provide a more detailed information within a stand. Thus, the proposed approach could provide a means to summarize site index in more homogeneous areas within a stand, even at sub-grid-cell scale.

One of the advantages of ITC approach is also the ability to characterize tree species for each tree with high accuracy since it is assumed that one crown segment is one tree (Paper II and III). While methods such as semi-ITC and ABA assume that there could be many species in the segment or grid, the species information is possible only through proportions of any forest attribute (e.g. species-specific volume) per each crown segment and grid-cell, respectively (Paper III) (Latifi et al., 2015). Knowing the species information for each tree, it is possible to develop species-specific models for any forest attribute, and this is important for forest inventory (Packalén and Maltamo, 2007, 2006). In this regard in Paper III, the ITC approach showed to provide high accuracies for minority species (even if with large systematic errors). This was also showed in a study by Ørka et al. (2013). The aggregated volume at grid-cell was affected by systematic error using ITC approach, while a high accuracy and low systematic error were achieved with the semi-ITC approach (Paper III). In this thesis, it was found that the semi-ITC approach provided prediction accuracies higher or similar to the ABA. This was also reported in earlier studies, comparing the semi-ITC and ABA approaches (Breidenbach et al., 2010; Rahlf et al., 2015). Thus, based on trade-off between RMSEs and mean differences, the volume predictions based on the semi-ITC approach outperformed the other approaches. In addition to the aforementioned species-specific studies, other studies compared predicted forest characteristics with ITC and ABA approaches and obtained comparable, higher or lower accuracies (Coomes et al., 2017; Latifi et al., 2015; Lee et al., 2017; Peuhkurinen et al., 2007; Yu et al., 2010). However, the forest type in Paper I was different from the other studies. Thus, this phenomenon also depend on the forest type, structure and the species present (Latifi et al., 2015).

Which spatial scale information should be provided and which approach is superior depends on the user's needs. In this thesis, the ITC approach provided means to accurate tree species identification, especially for minority species, and was a way to provide site index prediction with good accuracy. The semi-ITC approach seems to be the best choice to provide accurate species-specific attributes. The resulted forest characteristics can be aggregated at any other spatial scale (groups of trees, grids, and stands) with both approaches i.e. as it was done for the volume. This improved the knowledge of within-stand variation at any scale, especially for the minority species (Ørka et al., 2013). The only drawbacks of the ITC approach are the large systematic error unsuitable in operational forest inventories and the high cost of field surveys as tree positions are needed. The last statement also applies to the semi-ITC approach. However, methods for positioning trees using different methods are under development (Holopainen et al., 2014). In particular, detailed forest information obtained by ITC and semi-ITC can be used for improvements in forest management decisions, for example to optimize selection of silvicultural treatments (Wang et al., 2016), or for future tree-based growth simulations (Lo and Lin, 2013). Knowing the position of each tree can be important for many applications with sound ecological reasons, such as examination of habitat structure, distribution of dead trees (Dobbertin et al., 2001; Gillespie et al., 2008; Polewski et al., 2015), identification of invasive species (Dash et al., 2017), fire management (Morsdorf et al., 2004), and biomass estimation (Hauglin et al., 2013).

Table 3: Forest characteristics predicted in Papers I, II, and III with different spatial scales.

Spatial scale	Paper I	Paper II	Paper III
Tree	Tree positions, crown area, tree heights	Tree species, height, DBH, and age	Tree species, stem volume
Tree group	/	/	Total and species-specific volume
Grid-cell	/	Dominant height, species, age, and site index	Total and species-specific volume

7 Conclusion and further perspectives

This thesis demonstrated the potential to improve the prediction of forest characteristics with fusion of complementary 3D ALS and 2D hyperspectral data at different spatial scales. First, the fusion of complementary information derived from ALS and hyperspectral data was shown as a powerful basis for the discrimination of tree species, especially at tree level, which indirectly allows to reach high accuracies for species-specific models, such as height, DBH, volumes, and site index. The age was predicted with a moderate accuracy but there are still many unexplored fusions of ALS and hyperspectral data that could provide higher accuracies. Also, at grid-cell, the fusion of such data contributes to a high accuracy of species-specific forest characteristics for majority species. In contrast to abovementioned forest characteristics, the forest structural diversity measures were the only ones that in general did not gain in accuracy from the variable-level fusion of ALS and hyperspectral data. In addition, there is a huge lack of studies to make any conclusions about the benefits of such data fusion in different forest conditions, and in order to enlighten such data fusion properly, this subject should be further investigated in different environments. The acquisition costs of high-density ALS and the integration of LiDAR technology with hyperspectral sensors on the same platform are expected to decrease due to the technical advances in acquisition equipment. Recently, the hyperspectral ALS sensors have been developed with a high potential to be used as a future single-sensor solution for forest studies and mapping. However, they are still in the development stage and have not reached full maturity yet. Second, the evaluation of different spatial scales, via ITC and semi-ITC approaches, reached high accuracies for the site index, and total and species-specific volume determination, respectively. The accuracies of both forest characteristics were comparable with the ones obtained in the field and used in practice. Thus, the ITC and semi-ITC approaches have a high potential to map any forest characteristic to any scale that would help silviculturists and ecologists in their applications to facilitate their field work. In addition, the ITC approach was a successful method for the determination of the species-specific volume of minority species, but it resulted in too large systematic errors for all species to support forest inventories in contrast to the semi-ITC and ABA approaches. The advantage of the ITC and semi-ITC approaches, when large sample plots are observed, is that they can improve the estimation of certain forest characteristics as they directly take into account the variability within a forest stand. From such approaches, ecologists and silviculturists could profit greater knowledge to better model wildfires, monitor wildlife habitats, map aboveground carbon stock, describe growth dynamics, and formulate silvicultural strategies. As such approaches are more expensive due to more extensive field work, the combination of ABA and semi-ITC methods could further pave the way also for operational forest inventories by combining detection of individual trees in structurally complex and heterogeneous stands, with the ABA approach in homogeneous stands. Further studies are needed to examine the complementarity of different remotely sensed-based inventory approaches to obtain more knowledge about their benefits in different disciplines over larger areas.

References

Aguirre, O., Hui, G., Von Gadow, K., Jiménez, J., 2003. An analysis of spatial forest structure using neighbourhood-based variables. For. Ecol. Manage. 183, 137–145. doi:10.1016/S0378-1127(03)00102-6

Alonzo, M., Bookhagen, B., Roberts, D.A., 2014. Urban tree species mapping using hyperspectral and lidar data fusion. Remote Sens. Environ. 148, 70–83. doi:10.1016/j.rse.2014.03.018

Anderson, J.E., Plourde, L.C., Martin, M.E., Braswell, B.H., Smith, M.L., Dubayah, R.O., Hofton, M.A., Blair, J.B., 2008. Integrating waveform lidar with hyperspectral imagery for inventory of a northern temperate forest. Remote Sens. Environ. 112, 1856–1870. doi:10.1016/j.rse.2007.09.009

Asner, G., 2008. Hyperspectral remote sensing of canopy chemistry, physiology, and biodiversity in tropical rainforests, in: Hyperspectral Remote Sensing of Tropical and Sub-Tropical Forests. CRC Press, pp. 261–296. doi:10.1201/9781420053432.ch12

Asner, G.P., Knapp, D.E., Kennedy-Bowdoin, T., Jones, M.O., Martin, R.E., Boardman, J., Hughes, R.F., 2008. Invasive species detection in Hawaiian rainforests using airborne imaging spectroscopy and LiDAR. Remote Sens. Environ. 112, 1942–1955. doi:10.1016/j.rse.2007.11.016

Asner, G.P., Martin, R.E., Anderson, C.B., Knapp, D.E., 2015. Quantifying forest canopy traits: Imaging spectroscopy versus field survey. Remote Sens. Environ. 158, 15–27. doi:10.1016/j.rse.2014.11.011

Asner, G.P., Martin, R.E., Knapp, D.E., Tupayachi, R., Anderson, C.B., Sinca, F., Vaughn, N.R., Llactayo, W., 2017. Airborne laser-guided imaging spectroscopy to map forest trait diversity and guide conservation. Science (80-.). 355, 385–389. doi:10.1126/science.aaj1987

Baltsavias, E.P., 1999. Airborne laser scanning: basic relations and formulas. ISPRS J. Photogramm. Remote Sens. 54, 199–214. doi:10.1016/S0924-2716(99)00015-5

Bernstein, L.S., Adler-Golden, S.M., Sundberg, R.L., Levine, R.Y., Perkins, T.C., Berk, A., Ratkowski, A.J., Felde, G., Hoke, M.L., 2005. A new method for atmospheric correction and aerosol optical property retrieval for VIS-SWIR multi- and hyperspectral imaging sensors: QUAC (QUick Atmospheric Correction), in: International Geoscience and Remote Sensing Symposium (IGARSS). pp. 3549–3552. doi:10.1109/IGARSS.2005.1526613

Borengaser, M., Hungate, W.S., Watkins, R., 2008. Hyperspectral remote sensing-Principles and aplications. CRC Press Taylor & Francis Group, Boca Raton.

Boschetti, M., Boschetti, L., Oliveri, S., Casati, L., Canova, I., 2007. Tree species mapping with airborne hyper-spectral MIVIS data: the Ticino Park study case. Int. J. Remote Sens. 28, 1251–1261. doi:10.1080/01431160600928542

Breidenbach, J., Næsset, E., Lien, V., Gobakken, T., Solberg, S., 2010. Prediction of species specific forest inventory attributes using a nonparametric semi-individual tree crown approach based on fused airborne laser scanning and multispectral data. Remote Sens. Environ. 114, 911–924. doi:10.1016/j.rse.2009.12.004

Clark, M.L., Roberts, D.A., Ewel, J.J., Clark, D.B., 2011. Estimation of tropical rain forest aboveground biomass with small-footprint lidar and hyperspectral sensors. Remote Sens. Environ. 115, 2931–2942. doi:10.1016/j.rse.2010.08.029

Clawges, R., Vierling, K., Vierling, L., Rowell, E., 2008. The use of airborne lidar to assess avian species diversity, density, and occurrence in a pine/aspen forest. Remote Sens. Environ. 112, 2064–2073. doi:10.1016/j.rse.2007.08.023

Coomes, D.A., Dalponte, M., Jucker, T., Asner, G.P., Banin, L.F., Burslem, D.F.R.P., Lewis, S.L., Nilus, R., Phillips, O.L., Phua, M.-H., Qie, L., 2017. Area-based vs tree-centric approaches to mapping forest carbon in Southeast Asian forests from airborne laser scanning data. Remote Sens. Environ. 194, 77–88. doi:10.1016/j.rse.2017.03.017

Coops, N.C., 2015. Characterizing Forest Growth and Productivity Using Remotely Sensed Data. Curr. For. Reports 195–205. doi:10.1007/s40725-015-0020-x

Coops, N.C., Hilker, T., Wulder, M.A., St-Onge, B., Newnham, G., Siggins, A., Trofymow, J.A. (Tony), 2007. Estimating canopy structure of Douglas-fir forest stands from discrete-return LiDAR. Trees 21, 295–310. doi:10.1007/s00468-006-0119-6

Dalponte, M., Bruzzone, L., Gianelle, D., 2008. Fusion of hyperspectral and LIDAR remote sensing data for classification of complex forest areas. IEEE Trans. Geosci. Remote Sens. 46, 1416–1427. doi:10.1109/TGRS.2008.916480

Dalponte, M., Bruzzone, L., Gianelle, D., 2012. Tree species classification in the southern Alps based on the fusion of very high geometrical resolution multispectral/hyperspectral images and LiDAR data. Remote Sens. Environ. 123, 258–270. doi:10.1016/j.rse.2012.03.013

Dalponte, M., Ene, L.T., Marconcini, M., Gobakken, T., Næsset, E., 2015a. Semi-supervised SVM for individual tree crown species classification. ISPRS J. Photogramm. Remote Sens. 110, 77–87.

doi:10.1016/j.isprsjprs.2015.10.010

Dalponte, M., Ørka, H.O., Ene, L.T., Gobakken, T., Næsset, E., 2014. Tree crown delineation and tree species classification in boreal forests using hyperspectral and ALS data. Remote Sens. Environ. 140, 306–317. doi:10.1016/j.rse.2013.09.006

Dalponte, M., Ørka, H.O., Gobakken, T., Gianelle, D., Næsset, E., 2013. Tree species classification in boreal forests with hyperspectral data. IEEE Trans. Geosci. Remote Sens. 51, 2632–2645. doi:10.1109/TGRS.2012.2216272

Dalponte, M., Reyes, F., Kandare, K., Gianelle, D., 2015b. Delineation of individual tree crowns from ALS and hyperspectral data: a comparison among four methods. Eur. J. Remote Sens. 48, 365–382. doi:10.5721/EuJRS20154821

Dash, J., Pearse, G., Watt, M., Paul, T., 2017. Combining airborne laser scanning and aerial imagery enhances echo classification for invasive conifer detection. Remote Sens. 9, 156. doi:10.3390/rs9020156

Dash, J.P., Marshall, H.M., Rawley, B., 2015. Methods for estimating multivariate stand yields and errors using k-NN and aerial laser scanning. Forestry 88, 237–247. doi:10.1093/forestry/cpu054

Dobbertin, M., Baltensweiler, A., Rigling, D., 2001. Tree mortality in an unmanaged mountain pine (Pinus mugo var. uncinata) stand in the Swiss National Park impacted by root rot fungi. For. Ecol. Manage. 145, 79–89. doi:10.1016/S0378-1127(00)00576-4

Duncanson, L.I., Cook, B.D., Hurtt, G.C., Dubayah, R.O., 2014. An efficient, multi-layered crown delineation algorithm for mapping individual tree structure across multiple ecosystems. Remote Sens. Environ. 154, 378–386. doi:10.1016/j.rse.2013.07.044

Dye, M., Mutanga, O., Ismail, R., 2011. Examining the utility of random forest and AISA Eagle hyperspectral image data to predict Pinus patula age in KwaZulu-Natal, South Africa. Geocarto Int. 26, 275–289. doi:10.1080/10106049.2011.562308

Eitel, J.U.H., Höfle, B., Vierling, L.A., Abellán, A., Asner, G.P., Deems, J.S., Glennie, C.L., Joerg, P.C., LeWinter, A.L., Magney, T.S., Mandlburger, G., Morton, D.C., Müller, J., Vierling, K.T., 2016. Beyond 3-D: The new spectrum of lidar applications for earth and ecological sciences. Remote Sens. Environ. 186, 372–392. doi:10.1016/j.rse.2016.08.018

Ene, L., Næsset, E., Gobakken, T., 2012. Single tree detection in heterogeneous boreal forests using airborne laser scanning and area-based stem number estimates. Int. J. Remote Sens. 33, 5171–5193. doi:10.1080/01431161.2012.657363

Eysn, L., Hollaus, M., Lindberg, E., Berger, F., Monnet, Jean-Matthieu Dalponte, M., Kobal, M., Pellegrini, M., Lingua, E., Mongus, D., Pfeifer, N., 2015. A benchmark of lidar based single tree detection methods using heterogeneous forest data from the Alpine space. Forests 6, 1721–1747. doi:10.3390/f6051721

Fassnacht, F.E., Latifi, H., Koch, B., 2012. An angular vegetation index for imaging spectroscopy data—Preliminary results on forest damage detection in the Bavarian National Park, Germany. Int. J. Appl. Earth Obs. Geoinf. 19, 308–321. doi:10.1016/j.jag.2012.05.018

Fassnacht, F.E., Latifi, H., Stereńczak, K., Modzelewska, A., Lefsky, M., Waser, L.T., Straub, C., Ghosh, A., 2016. Review of studies on tree species classification from remotely sensed data. Remote Sens. Environ. 186, 64–87. doi:10.1016/j.rse.2016.08.013

Fassnacht, F.E., Neumann, C., Forster, M., Buddenbaum, H., Ghosh, A., Clasen, A., Joshi, P.K., Koch, B., 2014. Comparison of feature reduction algorithms for classifying tree species with hyperspectral data on three central European test sites. IEEE J. Sel. Top. Appl. Earth Obs.

Remote Sens. 7, 2547–2561. doi:10.1109/JSTARS.2014.2329390

Ferraz, A., Saatchi, S., Mallet, C.M., Jacquemoud, S., Gonçalves, G., Silva, C.A., Soares, P., Tomé, M., Pereira, L., 2016. Airborne lidar estimation of aboveground forest biomass in the absence of field inventory. Remote Sens. 8, 1–18. doi:10.3390/rs8080653

Franklin, S.E., Maudie, A.J., Lavigne, M.B., 2001. Using spatial co-occurrence texture to increase forest structure and species composition classification accuracy. Photogramm. Eng. Remote Sens. 67, 849–855.

Gallardo-Cruz, J.A., Meave, J.A., González, E.J., Lebrija-Trejos, E.E., Romero-Romero, M.A., Pérez-García, E.A., Gallardo-Cruz, R., Hernández-Stefanoni, J.L., Martorell, C., 2012. Predicting tropical dry forest successional attributes from space: Is the key hidden in image texture? PLoS One 7, 38–45. doi:10.1371/journal.pone.0030506

Geerling, G.W., Labrador-Garcia, M., Clevers, J.G.P.W., Ragas, a. M.J., Smits, A. J.M., 2007. Classification of floodplain vegetation by data fusion of spectral (CASI) and LiDAR data. Int. J. Remote Sens. 28, 4263–4284. doi:10.1080/01431160701241720

Gillespie, T.W., Brock, J., Wright, C.W., 2004. Prospects for quantifying structure, floristic composition and species richness of tropical forests. Int. J. Remote Sens. 25, 707–715. doi:10.1080/01431160310001598917

Gillespie, T.W., Foody, G.M., Rocchini, D., Giorgi, A.P., Saatchi, S., 2008. Measuring and modelling biodiversity from space. Prog. Phys. Geogr. 32, 203–221. doi:10.1177/0309133308093606

Guo, X., Coops, N.C., Tompalski, P., Nielsen, S.E., Bater, C.W., John Stadt, J., 2017. Regional mapping of vegetation structure for biodiversity monitoring using airborne lidar data. Ecol. Inform. 38, 50–61. doi:10.1016/j.ecoinf.2017.01.005

Hakkenberg, C.R., Song, C., Peet, R.K., White, P.S., Rocchini, D., 2016. Forest structure as a predictor of tree species diversity in the North Carolina Piedmont. J. Veg. Sci. 27, 1151–1163. doi:10.1111/jvs.12451

Hauglin, M., Dibdiakova, J., Gobakken, T., Næsset, E., 2013. Estimating single-tree branch biomass of Norway spruce by airborne laser scanning. ISPRS J. Photogramm. Remote Sens. 79, 147–156. doi:10.1016/j.isprsjprs.2013.02.013

Hernández-Stefanoni, J.L., Dupuy, J.M., Johnson, K.D., Birdsey, R., Tun-Dzul, F., Peduzzi, A., Caamal-Sosa, J.P., Sánchez-Santos, G., López-Merlín, D., 2014. Improving species diversity and biomass estimates of tropical dry forests using airborne LiDAR. Remote Sens. 6, 4741–4763. doi:10.3390/rs6064741

Hill, R. A., Thomson, A. G., 2005. Mapping woodland species composition and structure using airborne spectral and LiDAR data. Int. J. Remote Sens. 26, 3763–3779. doi:10.1080/01431160500114706

Hill, R., Hinsley, S., 2015. Airborne lidar for woodland habitat quality monitoring: Exploring the significance of lidar data characteristics when modelling organism-habitat relationships. Remote Sens. 7, 3446–3466. doi:10.3390/rs70403446

Hohenthal, J., Alho, P., Hyyppa, J., Hyyppa, H., 2011. Laser scanning applications in fluvial studies. Prog. Phys. Geogr. 35, 782–809. doi:10.1177/0309133311414605

Hollaus, M., Wagner, W., Eberhöfer, C., Karel, W., 2006. Accuracy of large-scale canopy heights derived from LiDAR data under operational constraints in a complex alpine environment. ISPRS J. Photogramm. Remote Sens. 60, 323–338. doi:10.1016/j.isprsjprs.2006.05.002

Holmgren, J., 2004. Prediction of tree height, basal area and stem volume in forest stands using airborne laser scanning. Scand. J. For. Res. 19, 543–553. doi:10.1080/02827580410019472

Holopainen, M., Kankare, V., Vastaranta, M., Liang, X., Lin, Y., Vaaja, M., Yu, X., Hyyppä, J., Hyyppä, H., Kaartinen, H., Kukko, A., Tanhuanpää, T., Alho, P., 2013. Tree mapping using airborne, terrestrial and mobile laser scanning - A case study in a heterogeneous urban forest. Urban For. Urban Green. 12, 546–553. doi:10.1016/j.ufug.2013.06.002

Holopainen, M., Vastaranta, M., Hyyppä, J., 2014. Outlook for the next generation's precision forestry in Finland. Forests 5, 1682–1694. doi:10.3390/f5071682

Hyyppä, J., Inkinen, M., 1999. Detecting and estimating attributes for single trees using laser scanner. Photogramm. J. Finl. 16, 27–42.

Ishii, H., McDowell, N., 2002. Age-related development of crown structure in coastal Douglas-fir trees. For. Ecol. Manage. 169, 257–270. doi:10.1016/S0378-1127(01)00751-4

Jones, T.G., Coops, N.C., Sharma, T., 2010. Assessing the utility of airborne hyperspectral and LiDAR data for species distribution mapping in the coastal Pacific Northwest, Canada. Remote Sens. Environ. 114, 2841–2852. doi:10.1016/j.rse.2010.07.002

Jung, J., Pekin, B.K., Pijanowski, B.C., 2013. Mapping open space in an old-growth, secondary-growth, and selectively-logged tropical rainforest using discrete return LIDAR. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 6, 2453–2461. doi:10.1111/j.1472-4642.2012.00928.x

Kaartinen, H., Hyyppä, J., 2008. EuroSDR/ISPRS Project, Commission II "Tree Extraction," Final Report. Dubline, Irland.

Kaartinen, H., Hyyppä, J., Yu, X., Vastaranta, M., Hyyppä, H., Kukko, A., Holopainen, M., Heipke, C., Hirschmugl, M., Morsdorf, F., Næsset, E., Pitkänen, J., Popescu, S., Solberg, S., Wolf, B.M., Wu, J.-C., 2012. An international comparison of individual tree detection and extraction using airborne laser scanning. Remote Sens. 4, 950–974. doi:10.3390/rs4040950

Kandare, K., Dalponte, M., Ørka, H., Frizzera, L., Næsset, E., 2017a. Prediction of species-specific volume using different inventory approaches by fusing airborne laser scanning and hyperspectral data. Remote Sens. 9, 400. doi:10.3390/rs9050400

Kandare, K., Ørka, H.O., Chan, J.C.W., Dalponte, M., 2016. Effects of forest structure and airborne laser scanning point cloud density on 3D delineation of individual tree crowns. Eur. J. Remote Sens. 49, 337–359. doi:10.5721/EuJRS20164919

Kandare, K., Ørka, H.O., Dalponte, M., Næsset, E., Gobakken, T., 2017b. Individual tree crown approach for predicting site index in boreal forests using airborne laser scanning and hyperspectral data. Int. J. Appl. Earth Obs. Geoinf. 60, 72–82. doi:10.1016/j.jag.2017.04.008

Kankare, V., Vastaranta, M., Holopainen, M., Räty, M., Yu, X., Hyyppä, J., Hyyppä, H., Alho, P., Viitala, R., 2013. Retrieval of forest aboveground biomass and stem volume with airborne scanning LiDAR. Remote Sens. 5, 2257–2274. doi:10.3390/rs5052257

Ke, Y., Quackenbush, L.J., 2011. A review of methods for automatic individual tree-crown detection and delineation from passive remote sensing. Int. J. Remote Sens. 32, 4725–4747. doi:10.1080/01431161.2010.494184

Koetz, B., Morsdorf, F., van der Linden, S., Curt, T., Allgöwer, B., 2008. Multi-source land cover classification for forest fire management based on imaging spectrometry and LiDAR data. For. Ecol. Manage. 256, 263–271. doi:10.1016/j.foreco.2008.04.025

Kokaly, R.F., Asner, G.P., Ollinger, S. V., Martin, M.E., Wessman, C.A., 2009. Characterizing canopy biochemistry from imaging spectroscopy and its application to ecosystem studies. Remote Sens. Environ. 113, S78–S91. doi:10.1016/j.rse.2008.10.018

Latifi, H., Fassnacht, F.E., Koch, B., 2012. Forest structure modeling with combined airborne hyperspectral and LiDAR data. Remote Sens. Environ. 121, 10–25. doi:10.1016/j.rse.2012.01.01

Latifi, H., Fassnacht, F.E., Müller, J., Tharani, A., Dech, S., Heurich, M., 2015. Forest inventories by LiDAR data: A comparison of single tree segmentation and metric-based methods for inventories of a heterogeneous temperate forest. Int. J. Appl. Earth Obs. Geoinf. 42, 162–174. doi:10.1016/j.jag.2015.06.008

Lausch, A., Erasmi, S., King, D., Magdon, P., Heurich, M., 2016. Understanding forest health with remote sensing - Part I—A review of spectral traits, processes and remote-sensing characteristics. Remote Sens. 8, 1029. doi:10.3390/rs8121029

Lausch, A., Heurich, M., Gordalla, D., Dobner, H.-J., Gwillym-Margianto, S., Salbach, C., 2013. Forecasting potential bark beetle outbreaks based on spruce forest vitality using hyperspectral remote-sensing techniques at different scales. For. Ecol. Manage. 308, 76–89. doi:10.1016/j.foreco.2013.07.043

Lee, A.C., Lucas, R.M., 2007. A LiDAR-derived canopy density model for tree stem and crown mapping in Australian forests. Remote Sens. Environ. 111, 493–518. doi:10.1016/j.rse.2007.04.018

Lee, J., Coomes, D., Schonlieb, C.-B., Cai, X., Lellmann, J., Dalponte, M., Malhi, Y., Butt, N., Morecroft, M., 2017. A graph cut approach to 3D tree delineation, using integrated airborne LiDAR and hyperspectral imagery.

Lefsky, M.A., Cohen, W.B., Acker, S.A., Parker, G.G., Spies, T.A., Harding, D., 1999. Lidar remote sensing of the canopy structure and biophysical properties of Douglas-fir western hemlock forests. Remote Sens. Environ. 70, 339–361. doi:10.1016/S0034-4257(99)00052-8

Li, M., Im, J., Quackenbush, L.J., Liu, T., 2014. Forest biomass and carbon stock quantification using airborne LiDAR data: A case study over Huntington wildlife forest in the Adirondack park. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 7, 3143–3156. doi:10.1109/JSTARS.2014.2304642

Listopad, C.M.C.S., Masters, R.E., Drake, J., Weishampel, J., Branquinho, C., 2015. Structural diversity indices based on airborne LiDAR as ecological indicators for managing highly dynamic landscapes. Ecol. Indic. 57, 268–279. doi:10.1016/j.ecolind.2015.04.017

Lo, C.-S., Lin, C., 2013. Growth-competition-based stem diameter and volume modeling for tree-level forest inventory using airborne LiDAR data. IEEE Trans. Geosci. Remote Sens. 51, 2216–2226. doi:10.1109/TGRS.2012.2211023

Luo, S., Wang, C., Xi, X., Pan, F., Peng, D., Zou, J., Nie, S., Qin, H., 2017. Fusion of airborne LiDAR data and hyperspectral imagery for aboveground and belowground forest biomass estimation. Ecol. Indic. 73, 378–387. doi:10.1016/j.ecolind.2016.10.001

Maltamo, M., Næsset, E., Vauhkonen, J., 2014. Forestry applications of airborne laser scanning, Managing Forest Ecosystems. Springer Netherlands, Dordrecht. doi:10.1007/978-94-017-8663-8

Maltamo, M., Packalén, P., Suvanto, A., Korhonen, K.T., Mehtätalo, L., Hyvönen, P., 2009. Combining ALS and NFI training data for forest management planning: a case study in Kuortane, Western Finland. Eur. J. For. Res. 128, 305–317. doi:10.1007/s10342-009-0266-6

Maltamo, M., Peuhkurinen, J., Malinen, J., Vauhkonen, J., Packalén, P., Tokola, T., 2009. Predicting tree attributes and quality characteristics of scots pine using airborne laser scanning data. Silva Fenn. 43, 507–521.

Manuri, S., Andersen, H., McGaughey, R.J., Brack, C., 2017. Assessing the influence of return density on estimation of lidar-based aboveground biomass in tropical peat swamp forests of Kalimantan, Indonesia. Int. J. Appl. Earth Obs. Geoinf. 56, 24–35. doi:10.1016/j.jag.2016.11.002

Martinuzzi, S., Vierling, L.A., Gould, W. a., Falkowski, M.J., Evans, J.S., Hudak, A.T., Vierling, K.T., 2009. Mapping snags and understory shrubs for a LiDAR-based assessment of wildlife habitat suitability. Remote Sens. Environ. 113, 2533–2546. doi:10.1016/j.rse.2009.07.002

McElhinny, C., Gibbons, P., Brack, C., Bauhus, J., 2005. Forest and woodland stand structural complexity: Its definition and measurement. For. Ecol. Manage. 218, 1–24. doi:10.1016/j.foreco.2005.08.034

McRoberts, R.E., Tomppo, E.O., 2007. Remote sensing support for national forest inventories. Remote Sens. Environ. 110, 412–419. doi:10.1016/j.rse.2006.09.034

Meng, J., Li, S., Wang, W., Liu, Q., Xie, S., Ma, W., 2016. Estimation of forest structural diversity using the spectral and textural information derived from SPOT-5 satellite images. Remote Sens. 8, 24. doi:10.3390/rs8020125

Morsdorf, F., Meier, E., Kötz, B., Itten, K.I., Dobbertin, M., Allgöwer, B., 2004. LIDAR-based geometric reconstruction of boreal type forest stands at single tree level for forest and wildland fire management. Remote Sens. Environ. 92, 353–362. doi:10.1016/j.rse.2004.05.013

Müller, J., Brandl, R., 2009. Assessing biodiversity by remote sensing in mountainous terrain: The potential of LiDAR to predict forest beetle assemblages. J. Appl. Ecol. 46, 897–905. doi:10.1111/j.1365-2664.2009.01677.x

Murray, H., Lucieer, A., Williams, R., 2010. Texture-based classification of sub-Antarctic vegetation communities on Heard Island. Int. J. Appl. Earth Obs. Geoinf. 12, 138–149. doi:10.1016/j.jag.2010.01.006

Næsset, E., 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. Remote Sens. Environ. 80, 88–99. doi:10.1016/S0034-4257(01)00290-5

Næsset, E., 2004. Practical large-scale forest stand inventory using a small-footprint airborne scanning laser. Scand. J. For. Res. 19, 164–179. doi:10.1080/02827580310019257

Næsset, E., Gobakken, T., Holmgren, J., Hyyppä, H., Hyyppä, J., Maltamo, M., Nilsson, M., Olsson, H., Persson, Å., Söderman, U., 2004. Laser scanning of forest resources: The nordic experience. Scand. J. For. Res. 19, 482–499. doi:10.1080/02827580410019553

Næsset, E., Økland, T., 2002. Estimating tree height and tree crown properties using airborne scanning laser in a boreal nature reserve. Remote Sens. Environ. 79, 105–115. doi:10.1016/S0034-4257(01)00243-7

Nagendra, H., Lucas, R., Honrado, J.P., Jongman, R.H.G., Tarantino, C., Adamo, M., Mairota, P., 2013. Remote sensing for conservation monitoring: Assessing protected areas, habitat extent, habitat condition, species diversity, and threats. Ecol. Indic. 33, 45–59. doi:10.1016/j.ecolind.2012.09.014

Neumann, M., Starlinger, F., 2001. The significance of different indices for stand structure and diversity in forests. For. Ecol. Manage. 145, 91–106. doi:10.1016/S0378-1127(00)00577-6

Niemann, K.O., 1995. Remote-sensing of forest stand age using airborne spectrometer data. Photogramm. Eng. Remote Sensing 61, 1119–1127.

Ørka, H.O., Dalponte, M., Gobakken, T., Næsset, E., Ene, L.T., 2013. Characterizing forest species composition using multiple remote sensing data sources and inventory approaches. Scand. J. For. Res. 28, 677–688. doi:10.1080/02827581.2013.793386

Ouma, Y.O., Tetuko, J., Tateishi, R., 2008. Analysis of co-occurrence and discrete wavelet transform textures for differentiation of forest and non-forest vegetation in very high resolution optical sensor imagery. Int. J. Remote Sens. 29, 3417–3456. doi:10.1080/01431160701601782

Ozdemir, I., Donoghue, D.N.M., 2013. Modelling tree size diversity from airborne laser scanning using canopy height models with image texture measures. For. Ecol. Manage. 295, 28–37. doi:10.1016/j.foreco.2012.12.044

Packalén, P., Maltamo, M., 2006. Predicting the plot volume by tree species using airborne laser scanning and aerial photographs. For. Sci. 52, 611–622.

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 Sens. Environ. 109, 328–341. doi:10.1016/j.rse.2007.01.005

Packalén, P., Temesgen, H., Maltamo, M., 2012. Variable selection strategies for nearest neighbor imputation methods used in remote sensing based forest inventory. Can. J. Remote Sens. 38, 557–569. doi:10.5589/m12-046

Pedersen, R.Ø., Bollandsås, O.M., Gobakken, T., Næsset, E., 2012. Deriving individual tree competition indices from airborne laser scanning. For. Ecol. Manage. 280, 150–165. doi:10.1016/j.foreco.2012.05.043

Persson, Å., Holmgren, J., Soderman, U., 2002. Detecting and measuring individual trees using an airborne laser scanner. Photogrametric Eng. Remote Sens. 68, 925–932.

Peuhkurinen, J., Maltamo, M., Malinen, J., Pitkänen, J., Packalén, P., 2007. Preharvest measurement of marked stands using airborne laser scanning. For. Sci. 53, 653–661.

Peuhkurinen, J., Mehtätalo, L., Maltamo, M., 2011. Comparing individual tree detection and the area-based statistical approach for the retrieval of forest stand characteristics using airborne laser scanning in Scots pine stands. Can. J. For. Res. 41, 583–598. doi:10.1139/X10-223

Polewski, P., Yao, W., Heurich, M., Krzystek, P., Stilla, U., 2015. Detection of fallen trees in ALS point clouds using a Normalized Cut approach trained by simulation. ISPRS J. Photogramm. Remote Sens. 105, 252–271. doi:10.1016/j.isprsjprs.2015.01.010

Pommerening, A., 2002. Approaches to quantifying forest structures. Forestry 75, 305–324. doi:10.1093/forestry/75.3.305

Pommerening, A., 2006. Evaluating structural indices by reversing forest structural analysis. For. Ecol. Manage. 224, 266–277. doi:10.1016/j.foreco.2005.12.039

Pretzsch, H., 2009. Forest dynamics, growth and yield: From Measurement to Model. Springer-Verlag Berlin Heidelberg, Berlin. doi:10.1007/978-3-540-88307-4

Racine, E.B., Coops, N.C., St-Onge, B., Begin, J., 2014. Estimating forest stand age from LiDAR-derived predictors and nearest neighbor imputation. For. Sci. 60, 128–136. doi:10.5849/forsci.12-088

Rahlf, J., Breidenbach, J., Solberg, S., Astrup, R., 2015. Forest parameter prediction using an image-based point cloud: A comparison of semi-ITC with ABA. Forests 6, 4059–4071. doi:10.3390/f6114059

Reitberger, J., Schnörr, C., Krzystek, P., Stilla, U., 2009. 3D segmentation of single trees exploiting full waveform LIDAR data. ISPRS J. Photogramm. Remote Sens. 64, 561–574. doi:10.1016/j.isprsjprs.2009.04.002

Rennolls, K., 1978. "Top Height"; its definition and estimation. Commonw. For. Rev. 57, 215–219.

Riaño, D., 2003. Modeling airborne laser scanning data for the spatial generation of critical forest parameters in fire behavior modeling. Remote Sens. Environ. 86, 177–186. doi:10.1016/S0034-4257(03)00098-1

Richter, R., Reu, B., Wirth, C., Doktor, D., 2016. The use of airborne hyperspectral data for tree species classification in a species-rich Central European forest area. Int. J. Appl. Earth Obs. Geoinf. 52, 464–474. doi:10.1016/j.jag.2016.07.018

Roberts, D.A., Green, R.O., Adams, J.B., 1997. Temporal and spatial patterns in vegetation and atmospheric properties from AVIRIS. Remote Sens. Environ. 62, 223–240. doi:10.1016/S0034-4257(97)00092-8

Ruiz, L.A., Hermosilla, T., Mauro, F., Godino, M., 2014. Analysis of the influence of plot size and LiDAR density on forest structure attribute estimates. Forests 5, 936–951. doi:10.3390/f5050936

Santos, M.J., Greenberg, J.A., Ustin, S.L., 2010. Using hyperspectral remote sensing to detect and quantify southeastern pine senescence effects in red-cockaded woodpecker (Picoides borealis) habitat. Remote Sens. Environ. 114, 1242–1250. doi:10.1016/j.rse.2010.01.009

Schaepman-Strub, G., Schaepman, M.E., Painter, T.H., Dangel, S., Martonchik, J.V., 2006. Reflectance quantities in optical remote sensing—definitions and case studies. Remote Sens. Environ. 103, 27–42. doi:10.1016/j.rse.2006.03.002

Scrinzi, G., Galvagni, D., Marzullo, L., 2010. I nuovi modelli dendrometrici per la stima delle masse assestamentali in Provincia di Trento. Provincia Autonoma di Trento - Servizio Foreste e Fauna, Trento.

Shang, X., Chisholm, L.A., 2014. Classification of Australian native forest species using hyperspectral remote sensing and machine-learning classification algorithms. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 7, 2481–2489. doi:10.1109/JSTARS.2013.2282166

Sharma, R.P., Brunner, A., Eid, T., Øyen, B.H., 2011. Modelling dominant height growth from national forest inventory individual tree data with short time series and large age errors. For. Ecol. Manage. 262, 2162–2175. doi:10.1016/j.foreco.2011.07.037

Skovsgaard, J.P., Vanclay, J.K., 2008. Forest site productivity: A review of the evolution of dendrometric concepts for even-aged stands. Forestry 81, 13–31. doi:10.1093/forestry/cpm041

Solberg, S., Næsset, E., Bollandsås, O.M., 2006. Single tree segmentation using airborne laser scanner data in a structurally heterogeneous spruce forest. Photogramm. Eng. Remote Sens. 72, 1369–1378. doi:0099-1112/06/7212–1369

St-Onge, B., Vega, C., Fournier, R. a., Hu, Y., 2008. Mapping canopy height using a combination of digital stereo-photogrammetry and lidar. Int. J. Remote Sens. 29, 3343–3364. doi:10.1080/01431160701469040

Stephens, P.R., Kimberley, M.O., Beets, P.N., Paul, T.S.H., Searles, N., Bell, A., Brack, C., Broadley, J., 2012. Airborne scanning LiDAR in a double sampling forest carbon inventory. Remote Sens. Environ. 117, 348–357. doi:10.1016/j.rse.2011.10.009

Strîmbu, V.F., Strîmbu, B.M., 2015. A graph-based segmentation algorithm for tree crown extraction using airborne LiDAR data. ISPRS J. Photogramm. Remote Sens. 104, 30–43.

doi:10.1016/j.isprsjprs.2015.01.018

Swatantran, A., Dubayah, R., Roberts, D., Hofton, M., Blair, J.B., 2011. Mapping biomass and stress in the Sierra Nevada using lidar and hyperspectral data fusion. Remote Sens. Environ. 115, 2917–2930. doi:10.1016/j.rse.2010.08.027

Tesfamichael, S.G., Ahmed, F.B., Van Aardt, J.A.N., 2010. Investigating the impact of discrete-return lidar point density on estimations of mean and dominant plot-level tree height in Eucalyptus grandis plantations. Int. J. Remote Sens. 31, 2925–2940. doi:10.1080/01431160903144086

Tonolli, S., Dalponte, M., Vescovo, L., Rodeghiero, M., Bruzzone, L., Gianelle, D., 2010. Mapping and modeling forest tree volume using forest inventory and airborne laser scanning. Eur. J. For. Res. 130, 569–577. doi:10.1007/s10342-010-0445-5

Torabzadeh, H., Morsdorf, F., Schaepman, M.E., 2014. Fusion of imaging spectroscopy and airborne laser scanning data for characterization of forest ecosystems – A review. ISPRS J. Photogramm. Remote Sens. 97, 25–35. doi:10.1016/j.isprsjprs.2014.08.001

Ung, C.H., Bernier, P.Y., Raulier, F., Fournier, R.A., Lambert, M.C., Régnière, J., 2001. Biophysical site indices for shade tolerant and intolerant boreal species. For. Sci. 47, 83–95.

Ustin, S.L., Roberts, D.A., Gamon, J.A., Asner, G.P., Green, R.O., 2004. Using imaging spectroscopy to study ecosystem processes and properties. Bioscience 54, 523. doi:10.1641/0006-3568(2004)054[0523:UISTSE]2.0.CO;2

Vaglio Laurin, G., Chen, Q., Lindsell, J.A., Coomes, D.A., Frate, F. Del, Guerriero, L., Pirotti, F., Valentini, R., 2014. Above ground biomass estimation in an African tropical forest with lidar and hyperspectral data. ISPRS J. Photogramm. Remote Sens. 89, 49–58. doi:10.1016/j.isprsjprs.2014.01.001

Valbuena, R., Maltamo, M., Marti-Fernandez, S., Packalen, P., Pascual, C., Nabuurs, G.J., 2013. Patterns of covariance between airborne laser scanning metrics and Lorenz curve descriptors of tree size inequality. Can. J. Remote Sens. 39. doi:10.5589/m13-012

van Aardt, J.A.N., Wynne, R.H., 2007. Examining pine spectral separability using hyperspectral data from an airborne sensor: An extension of field-based results. Int. J. Remote Sens. 28, 431–436. doi:10.1080/01431160500444772

Varvia, P., Lähivaara, T., Maltamo, M., Packalen, P., Tokola, T., Seppänen, A., 2016. Uncertainty quantification in ALS-based species-specific growing stock volume estimation. IEEE Trans. Geosci. Remote Sens. in process, 1–11. doi:10.1109/TGRS.2016.2628960

Vauhkonen, J., Seppänen, A., Packalén, P., Tokola, T., 2012. Improving species-specific plot volume estimates based on airborne laser scanning and image data using alpha shape metrics and balanced field data. Remote Sens. Environ. 124, 534–541. doi:10.1016/j.rse.2012.06.002

Voss, M., Sugumaran, R., 2008. Seasonal effect on tree species classification in an urban environment using hyperspectral data, LiDAR, and an object-oriented approach. Sensors 8, 3020–3036. doi:10.3390/s8053020

Wang, Y., Hyyppä, J., Liang, X., Kaartinen, H., Yu, X., Lindberg, E., Holmgren, J., Qin, Y., Mallet, C., Ferraz, A., Torabzadeh, H., Morsdorf, F., Zhu, L., Liu, J., Alho, P., 2016. International benchmarking of the individual tree detection methods for modeling 3-D canopy structure for silviculture and forest ecology using airborne laser scanning. IEEE Trans. Geosci. Remote Sens. 54, 5011–5027. doi:10.1109/TGRS.2016.2543225

Wehr, A., Lohr, U., 1999. Airborne laser scanning - an introduction and overview. ISPRS J. Photogramm. Remote Sens. 54, 68–82. doi:10.1016/S0924-2716(99)00011-8

White, J.C., Coops, N.C., Wulder, M.A., Vastaranta, M., Hilker, T., Tompalski, P., 2016. Remote sensing technologies for enhancing forest inventories: A review. Can. J. Remote Sens. 42, 619–641. doi:10.1080/07038992.2016.1207484

Wing, B.M., Ritchie, M.W., Boston, K., Cohen, W.B., Gitelman, A., Olsen, M.J., 2012. Prediction of understory vegetation cover with airborne lidar in an interior ponderosa pine forest. Remote Sens. Environ. 124, 730–741. doi:10.1016/j.rse.2012.06.024

Yao, W., Krull, J., Krzystek, P., Heurich, M., 2014. Sensitivity analysis of 3D individual tree detection from LiDAR point clouds of temperate forests. Forests 5, 1122–1142. doi:10.3390/f5061122

Yu, B., Ostland, I.M., Gong, P., Pu, R.L., 1999. Penalized discriminant analysis of in situ hyperspectral data for conifer species recognition. IEEE Trans. Geosci. Remote Sens. 37, 2569–2577. doi:10.1109/36.789651

Yu, X., Hyyppä, J., Holopainen, M., Vastaranta, M., 2010. Comparison of area-based and individual tree-based methods for predicting plot-level forest attributes. Remote Sens. 2, 1481–1495. doi:10.3390/rs2061481

Yu, X., Hyyppä, J., Karjalainen, M., Nurminen, K., Karila, K., Vastaranta, M., Kankare, V., Kaartinen, H., Holopainen, M., Honkavaara, E., Kukko, A., Jaakkola, A., Liang, X., Wang, Y., Hyyppä, H., Katoh, M., 2015. Comparison of laser and stereo optical, SAR and InSAR point clouds from air- and space-borne sources in the retrieval of forest inventory attributes. Remote Sens. 7, 15933–15954. doi:10.3390/rs71215809

Yu, X., Hyyppä, J., Vastaranta, M., Holopainen, M., Viitala, R., 2011. Predicting individual tree attributes from airborne laser point clouds based on the random forests technique. ISPRS J. Photogramm. Remote Sens. 66, 28–37. doi:DOI: 10.1016/j.isprsjprs.2010.08.003

Zhang, J., 2010. Multi-source remote sensing data fusion: status and trends. Int. J. Image Data Fusion 1, 5–24. doi:10.1080/19479830903561035

Paper I Kandare, K., Ørka, H.O., Chan, J.C.W. & Dalponte, M. 2017. Effects of forest structure and airborne laser scanning point cloud density on 3D delineation of individual tree crowns. - European Journal of Remote Sensing 49: 337-359. DOI: 10.5721/EuJRS20164919
Paper II Kandare, K., Ørka, H.O., Dalponte, M., Næsset, E. & Gobakken, T. 2017. Individual tree crown approach for predicting site index in boreal forests using airborne laser scanning and hyperspectral data. - International Journal of Applied Earth Observation and Geoinformation 60: 72-82. DOI: 10.1016/j.jag.2017.04.008
Paper III Kandare, K., Dalponte, M., Ørka, H., Frizzera, L. & Næsset, E. 2017. Prediction of species-specific volume using different inventory approaches by fusing airborne laser scanning and hyperspectral data. - Remote Sensing 9(5): 400, 19 pp. DOI: 10.3390/rs9050400
Paper IV Kandare, K., Riccadonna, S., Franceschi, P., Ørka, H.O. & Dalponte, M. Fusion of airborne laser scanning and hyperspectral data for assessing forest structural diversity indices. (Manuscript)

ISBN: 978-82-575-1452-5
ISSN: 1894-6402

FONDAZIONE EDMUND MACH

Foundation Edmund Mach

Research and Innovation Center
Foxlab group
Via E. Mach 1
I-38010 San Michele all'Adige (TN)
Italy
www.fmach.it/eng

NMBU

Norwegian University of Life Sciences

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