Tree Species Classification

Analyzing Multitemporal Satellite Imagery and Multispectral Airborne Laser Scanning Data

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Abstract

Tree species composition of forests affects the whole ecosystem and is part of the information needed for an efficient planning of forest management. This thesis explores how recent developments in remote sensing can provide more accurate tree species mapping. I try to answer the question of how the properties of these data can be used to derive more information on tree species. Out of the four papers in this thesis, two papers examine how multitemporal satellite imagery from the Sentinel-2 mission can be of use, and the other two papers investigate what properties of multispectral airborne laser scanning (MSALS) data that contain the most information on tree species. We applied a Bayesian method to multitemporal satellite imagery for tree species classification of pixels in the hemiboreal forest of Remningstorp in southwestern Sweden. The Bayesian method was applied to 142 Sentinel-2 images, and to a subset of images ranked and selected by the separability of tree species classes. The method was also compared to a Random Forest classifier for 45 Sentinel-2 images of boreal forest in mid-Sweden. The Bayesian method performed better for homogeneous tree species classes, while Random Forest performed better for heterogeneous classes. Data from two MSALS systems were used for classifying the tree species of individual trees. Optech Titan-X data were used to classify free-standing trees of nine species in Remningstorp. By using Riegl VQ-1560i-DW data, we performed a tree species classification in a more operational setting for three tree species in closed-canopy hemiboreal forest in Asa in southern Sweden. Multispectral intensity features provided a great improvement in classification accuracy in both cases, compared to using only structural features or combining them with monospectral intensity features. For Optech Titan-X, the green wavelength performed poorly, but for Riegl VQ-1560i-DW, the green wavelength provided the most information for separability, especially for birch (Betula spp.). There are two main conclusions in this thesis. The first is that Bayesian methods that updates probabilities as new observations are made provides an opportunity to automate the addition of satellite images for an updated classification. The second is that MSALS data provides more information on tree species than monospectral data and tree crown structure do, with the most information coming from the upper parts of the canopy. Nonetheless, what wavelengths of light that contribute most to tree species classification accuracy is highly dependent on what MSALS system that is used.

Keywords: ALS, area-based, Bayesian, ITC, LiDAR, indvidual trees, land cover, time series

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Populärvetenskaplig sammanfattning

För att kunna förvalta våra ekosystem i enlighet med uppsatta mål krävs tillförlitlig information som beskriver ekosystemet och dess förändringar. Vi behöver t.ex. veta var olika åtgärder bör utföras och framförallt var inga åtgärder bör utföras. För att kunna planera skogsbruket rationellt kan vi använda oss av uppgifter som tas fram med hjälp av fjärranalys, där man mäter skogen med olika sensorer och system på avstånd. Med flygplan och satelliter kan datainsamlingen ske effektivt för stora områden.

En snabb teknikutveckling har gett stora möjligheter att använda fjärranalysdata från tidsserier, med hög upplösning, och från olika sensorer. Den här avhandlingen handlar om trädslagsklassning med hjälp av data från några fjärranalyssystem vars egenskaper gör det troligt att de kan ge information om trädslag.

I två av studierna har vi använt täta tidsserier av Sentinel-2-satellitbilder som har potential att fånga skillnader i olika trädslags utseende baserat på årstidernas växlingar. Genom att använda Bayesianska metoder har vi kunnat använda de upprepade mätningarna från Sentinel-2 för att löpande uppdatera sannolikheten att ett visst trädslag finns på en viss plats.

I de två andra studierna använde vi data från två olika flygburna laserskannrar som mäter skogen med hjälp av tre respektive två våglängder av laserljus, så kallade multispektrala data. Vid laserskanning mäts tredimensionella koordinater in från vegetationen, marken och andra objekt. Dessa kallas punkter. Om mätningarna görs tillräckligt tätt kan enskilda trädkronor avgränsas från data. Multispektrala data kan göra det möjligt att skilja på olika trädslag eftersom trädslagen har något olika färger.

Vi delade upp punkterna utifrån var i trädkronorna de fanns. På sätt kunde vi avgöra var i trädkronorna mest information om trädslag kom från. Vi undersökte också hur de olika våglängderna av laserljus påverkade klassningsnoggrannheten.

Slutsatserna som kan dras utifrån den här avhandlingen är, för det första att den Bayesianska metoden är ett effektivt sätt att klassa trädslag med hjälp av en tidsserie av satellitbilder, och för det andra att de övre delarna av krontaket innehåller mest färginformation som kan kopplas till trädslag. De två laserskanningssystemen som användes gav olika resultat när det gällde olika färger på laserljus. Gemensamt är likväl att laserljus i flera färger bidrog till trädslagsklassningen.

Just nu är multispektral laserskanning en teknik som inte riktigt är mogen för operationell användning. Likväl fortgår utvecklingen och i en inte alltför avlägsen framtid kan dessa system komma att användas för nationella skanningar. Detta förutsätter att systemen kan flygas på en tillräckligt hög höjd för att datainsamlingen ska bli rationell samtidigt som de levererar högupplösta data. Satellitbilder har länge nyttjats till att göra observationer och producera kartor på en global skala. Med så täta observationer i tid som Sentinel-2 satelliterna gör finns möjligheten att utnyttja årstidsberoende fenomen för att förbättra klassningsnoggrannheter. I en värld där utvecklingen snabbt och stadigt går framåt, kommer vi att se fler och fler system som kan mäta skog, både ofta och med hög upplösning. Genom att ta vara på dessa nya egenskaper i data, kommer vi kunna ta fram bättre trädslagskartor och därmed ta bättre beslut i framtiden.

To my family: Sofie, Ingvild, Göran and Einar.

Metrodorus initio libri, qui est de natura: 'Nego,' inquit, 'scire nos sciamusne aliquid an nihil sciamus, ne id ipsum quidem, nescire aut scire, scire nos, nec omnino sitne aliquid an nihil sit.'

Cicero, *Academica* 2.73

Metrodorus, at the beginning of his volume *On Nature* says: 'I deny that we know whether we know something or know nothing, and even that we know the mere fact that we do not know (or do know), or know at all whether something exists or nothing exists.'

Translated by Harris Rackham, 1933

Preface

Dear Reader,
welcome to my thesis. As you can see from these first words, I have chosen to make this introductory chapter a bit more personal than what is common. The reasoning behind this is that I believe that every researcher and scientist affects their research by simply being who they are. The researcher has their own view of things, the scientist chooses what is interesting to themselves and they choose what hypotheses to test. Just look at me, starting my thesis on my *beliefs*. Maybe the fact that I would do such a thing points to something that has affected my research. I hope that this introduction to me as a researcher can help you to determine whether or not my research and the results thereof are to be trusted. If you're interested in scrutinizing the work, the details are presented in each paper.

Speaking of beliefs and philosophy, there are several different views on what makes science *science*. We have views like that of Karl Popper, who claimed that science necessarily needs to be falsifiable, or like that of Thomas Kuhn who claimed that "normal" science is the process of solving the puzzle of how the world works. In the studies that I've written or taken part in writing, I cannot say that I've falsified anything, but maybe I've spent some time trying to solve this puzzle.

The title of this thesis, *Tree Species Classification*, is very broad and still specific at the same time. Even though individual trees might be of interest, it's the composition of the forest that is of interest for ecologists and foresters. Therefore, I'd like to present what I think of the Swedish forest and forestry. The Swedish word *Skogen* can be translated as *the forest* or *the woods*, but in a way it's larger than that. The forest of northern Sweden feels almost never-ending, it's the default state, and fields or settlements are the exception. In northern Sweden, there are very few individual woods with specific names, it's all just *Skogen*. Often, if there are names ending in *skogen* it's probably something else than a forest, like a nature reserve, a village, or a system of trails. When walking in the woods of northern Sweden, I feel a similar feeling as when looking out over the Atlantic ocean. It gives a feeling of endlessness; a vastness stretching out beyond the horizon. I find many things in the forest: mushrooms, berries, relaxation, beauty and more, just like others also do. These are important values that the forest provides and I think they need to be protected so that they can be available for everyone in the future. Forestry is a very long game, trees can live for half a millennium or more. The forestry measures we undertake today will result in long standing effects on people, landscapes and ecosystems. So if we humans want to be good stewards for the natural resources of our planet, and if we want to do this in a sustainable way, then we need information.

For the past few years, I've been looking at how we can find tree species information in remote sensing data. To do this, I've tried my best to only use Free and Open Source Software (FOSS). I believe that results from publicly funded research should be freely available to the public and that we should take care in choosing software that is also freely available for everyone. These arguments for the use of FOSS are in the same vein as those for open access publishing of scientific results. All the papers in this thesis are either published as open access or will be published as open access papers. As a part in this, I've tried to make this thesis as readable and understandable as possible for my family: my wife, parents, and brother.

Contents

List of Publications

This thesis is based on the work contained in the following papers, referred to by Roman numerals in the text:

I Arvid Axelsson, Eva Lindberg, and Håkan Olsson (2018). Exploring Multispectral ALS Data for Tree Species Classification. *Remote Sensing* 10(2):183.

II Arvid Axelsson, Eva Lindberg, Heather Reese, and Håkan Olsson (2021). Tree species classification using Sentinel-2 imagery and Bayesian inference. *International Journal of Applied Earth Observation and Geoinformation* 100, August 2021, 102318.

III Giovanni D'Amico, Mats Nilsson, Arvid Axelsson, and Gherardo Chirici (n.d). Data Homogeneity Impact in Bayesian Inference Tree Species Classification Based on Sentinel-2 Multitemporal Data (Manuscript)

IV Arvid Axelsson, Eva Lindberg, and Johan Holmgren (n.d). Tree Species Classification in Closed-Canopy Forest Using Multispectral Airborne Laser Data (Manuscript)

The contribution of Arvid Axelsson to the papers included in this thesis was as follows:

I Developed the research idea together with co-authors, performed field inventory, performed data processing, performed statistical analysis, and wrote the manuscript with support from the co-authors.

II Developed the research idea together with co-authors, developed classification method together with co-authors, implemented this method in program code, performed statistical analysis, and wrote the manuscript together with the co-authors.

III Provided information and explained the classification method, produced example code for classification with one of the methods used in the paper, participated in writing methods and overall editing of the manuscript.

IV Developed the research idea and methods together with co-authors, performed data processing in concert with the co-authors, performed statistical analysis, and wrote the manuscipt together with the co-authors.

Abbreviations

AI	Artificial Intelligence
ALS	Airborne Laser Scanning
DEM	Digital Elevation Model
FOSS	Free and Open Source Software
GSD	Ground Sampling Distance
HMM	Hidden Markov Model
ITC	Individual Tree Crown
LDA	Linear Discriminant Analysis
LULC	Land Use and Land Cover
LiDAR	Light Detection and Ranging
ML	Machine Learning
MSALS	Multispectral Airborne Laser Scanning
NFI	National Forest Inventory
NIR	Near Infrared
RF	Random Forest
SPL	Single Photon LiDAR
SWIR	Short Wave Infrared

1 Introduction

There are many important and pressing problems in the world today, from war and famine to global climate change. Many of these problems involve the way we humans manage our resources. Even though it's only a small thread in a tapestry of everything that is made to make things better, the remote sensing community tries to provide some information as a basis for making more informed decisions. Knowledge of the geographic location and extent of different ecosystems are key to understand where and how forest management for wood biomass production might be exercised, and where nature conservation or management for ecological values are needed.

Since forests are ecosystems, there are infinitely many variables that can be of interest for planners. Everything from soil wetness, to species composition among saprophytic fungi, and the human experience of walking in the woods. I've chosen to focus on new developments in remote sensing data and how these data may be interpreted to improve on automatic tree species mapping. Even though I gravitated to this subject area due to my own interest in forestry and technology, there has also been calls from the forest sector for better and higher resolution tree species mapping (Eva Lindberg et al., n.d.).

The tree species composition of a forest is not only affected by the ecosystem, but also affects the ecosystem composition. Many species, especially among those that are on the red list, are highly dependent on the tree species composition of their habitat. Some examples are the white-backed woodpecker (*Dendrocopos leucotos*) and the beetle *Tragosoma depsarium*. As humans, our actions and activities impact the tree species composition of forests and by extension the whole ecosystem surrounding these trees.

Generally, the goal of forest remote sensing would be to provide data for planning of forestry, nature conservation planning and developing of policy. It is a research area dependent on the development within other areas, such as that of sensors and electronics, where new devices for measuring the reality are developed, and computing and statistics, where new methods for extracting information from data are developed. Remote sensing of forest is when measurements of forest properties are made from afar. The properties are often measured indirectly via some informative feature of data gathered by a sensor. If done successfully, remote sensing could aid in management planning by locating and quantifying the values of the forest. In the end, this resource management boils down to economics and how we choose between the different values that the forest can provide, and an accurate assessment of these values are of the highest importance.

1.1 Remote Sensing

Over the past decades there have been many efforts in remote sensing and land use and land cover (LULC) classification, part of it being tree species classification. Up until fairly recently, operational tree species mapping was made manually using aerial photographs. In this case, whole stands were classified by looking at both tree shape and color but also by taking other factors, such as estimated hydrology, into account (Ihse, Rafstedt, and Wastenson, 1993). For the last couple of decades, digital images have been used, that have provided the opportunity of a more automated workflow (Goodbody, Coops, and White, 2019; Puliti et al., 2017). Nonetheless, when it comes to tree species classification, visual interpretation of aerial photographs is still very much needed (Kangas et al., 2018). This might be especially true for more uncommon tree species and land cover types, where a solid foundation of reference data is missing.

When making estimations of the forest from remote sensing data, it's important to also have reference data to relate the measurements to. What we actually might measure is a pixel value or a coordinate of some surface reflecting light. Oftentimes, these measurements are not what we're actually interested in. What we want to know is a property of the object that these measurements represent. To go from remote sensing data to a tree species (property) classification of a tree (object), we need to relate the remote sensing data to the species. To do this, we need to know where some trees are located and their tree species. This can be done by conducting a field inventory or by, in some cases, using higher resolution remote sensing data (Persson, Olofsson, and Holmgren, 2022).

How remote sensing data is collected can be divided by sensor type and platform. Sensors are, for example, photographic cameras (Gini et al., 2012), electro-optical scanners (Deur, Gašparović, and Balenović, 2020; Persson, Lindberg, and Reese, 2018), radar (Radio Detection and Ranging) (Gillespie et al., 2009; Wollersheim, Collins, and Leckie, 2011), and LiDAR (Light Detection and Ranging) (Qin et al., 2022; Yang et al., 2023; Yu et al., 2017). Each sensor is either active or passive. An active sensor emits a signal that is then reflected by an object, and the reflected signal is measured. A passive sensor relies on another source of electromagnetic radiation, usually the sun, that emits light which is then reflected and measured. Platforms carrying the sensor can be satellites, manned aircraft, drones, or some terrestrial carrier. Combinations of almost all of these sensors and platforms have at some point been used for tree species classification. For the papers in this theses, my co-authors and I have used multitemporal optical satellite data and multispectral airborne laser scanning (MSALS) data.

To classify tree species from remote sensing data, researchers have used several different methods, such as Linear Discriminant Analysis (LDA) (e.g., Brandtberg, 2007; Lindberg et al., 2014), support vector machines (e.g., Dalponte et al., 2013; Deur, Gašparović, and Balenović, 2020; Kluczek, Zagajewski, and Zwijacz-Kozica, 2023; Lin and Herold, 2016), and Random Forest (RF) (e.g., Immitzer, Atzberger, and Koukal, 2012; Ma et al., 2021; Matikainen, Hyyppä, and Litkey, 2016). Of course, there are a multitude of different classification methods that have been used by other authors, but I can't possibly list them all here.

My research has revolved around creating solutions for an automatic tree species classification from measurements made from airborne or satellite-borne sensors. The methods I've tested have all focused on species-specific spectral properties. When I've worked with optical satellite imagery, I've focused on using the high temporal resolution that is provided. When using MSALS data, I've looked at spectral properties of different tree species and how the three-dimensionality of data can make it easier to locate the spectral properties within the tree crowns. Both types of data provide both challenges and unique opportunities.

1.1.1 Aggregated or Individual Tree Species

To use remote sensing data that have been gathered, there are two main ways to relate them to what's on the ground. One is the so called *area-based* method and the other is the *individual tree crown* (ITC) method (Maltamo, Næsset, and Vauhkonen, 2014). There are also hybrid methods (e.g., Breidenbach et al., 2010; Lindberg et al., 2010; Rahlf et al., 2015) that combine elements of both the area-based and ITC methods. In the area-based method, aggregate stand properties of the forest in an area unit are related to aggregate properties of remote sensing data from the same area unit (Næsset and Bjerknes, 2001). When using ITC methods, data are aggregated for each tree crown, and then descriptive features of those data are related to properties of the tree.

Data with a spatial resolution such that single measurements can include several trees, can only be used to make estimates of aggregate properties, since the measurement itself is of an aggregate property. If the aspiration is to estimate tree specific properties, such as species, data with higher spatial resolution are needed. A high resolution is in this case many measurements (i.e., samples) from each tree crown (Lindberg and Holmgren, 2017). When using high-resolution data, one can choose to use either ITC methods or an area-based approach. In the case of tree species classification, the tree species is a tree specific property, while tree species composition is the stand level aggregate property. These are not comparable properties! Since a tree is of a certain species, there is no in-between; the species is a nominal value. In contrast, a tree species composition is a continuous value that can represent the proportion of stems, canopy cover, basal area, or stem volume.

1.1.2 Satellite Imagery

Optical satellite data is exactly what it sounds like. You essentially put a camera in space and take pictures of Earth's surface. Of course, there are some differences between consumer cameras and the passive-optical scanners that can be attached to a satellite. Unlike most cameras, many sensors scan the surface rather than taking a snapshot in a square format, and they may provide additional spectral bands. The images produced are, just like pictures taken using an ordinary digital camera, made up of pixels whose values are some average of the area being depicted.

Satellite imagery (i.e., data from a passive optical sensor attached to a satellite) have been used in forest mapping since the first satellite images became available to the public in the 1970:s with data from the Landsat 1 satellite (Elifrits, Barr, and Johannsen, 1978). The technological development has since then allowed for higher resolution imagery, both temporally and spatially, to a lower price, and many tree species classification efforts have been made using satellite imagery (Deur, Gašparović, and Balenović, 2020; Immitzer, Atzberger, and Koukal, 2012; Persson, Lindberg, and Reese, 2018). In several of these classification attempts, color (i.e., spectral) difference between tree species have been used to discriminate by. Other authors have also used textural features or a combination of spectral and textural properties (Fassnacht et al., 2016).

Each pixel of a satellite image can represent a fairly large area of the ground, a property referred to as the ground sampling distance (GSD; i.e., the center-to-center distance between pixels in the same line or row as measured on the ground). This is the spatial resolution of the satellite image. A 30 cm GSD is available from some commercial satellites, and is considered to be very high spatial resolution. This kind of resolution is not common and most freely available medium-resolution satellite data has a GSD of around 10 m to 30 m (e.g., data from the Landsat 9 and Sentinel-2 satellites).

In terms of tree species classification, data with a GSD of 10 m to 30 m are fairly coarse. Spectral reflectance differ between tree species, not only at a leaf-level (Hovi, Raitio, and Rautiainen, 2017), but also due to tree crown structure (Asner, 1998). The leaves are small, the tree crowns are larger, but the pixels are larger still. When data as coarse as these are used, the reflected light measured is not from a single tree. Two trees standing next to each other may be of different species, but both can affect the pixel value of the same pixel. This is called a *mixed pixel* and it can pose a problem, because what, for example, is the species that lies in between pine and birch? One solution is to put these dissimilar field plots, with different forms of mixed forest and the corresponding pixels, into a *mixed*-class.

There is also the problem of the background, or rather, just the ground. Since tree crowns don't provide a complete cover of the ground, some light reflected from the field layer (e.g., grasses, ferns, low growing shrubs, and so on) will get through to the sensor (Asner, 1998). This light also mixes with that which is reflected by the trees and therefore also affects the resulting pixel value. Another phenomenon that affect the images are shadows. These areas are darker, not because they reflect less of the light that falls upon them, but because there is less light there to reflect. Nevertheless, the species composition of trees within a pixel normally affects the pixel value greatly, making tree species classification possible.

Some of the spectral differences between species may also change as an effect of seasonal or environmental factors (Fassnacht et al., 2022). With the difference in and seasonal change of species-specific spectral characteristics, multitemporal satellite imagery makes for a great data source. Ratios such as the Normalized Difference Vegetation Index (NDVI), that is a measure of the reflected near-infrared (NIR) light normalized by the reflected red light, can be used to not only separate vegetation from other land cover types (Lillesand, Kiefer, and Chipman, 2007), but also to estimate seasonal change (Jonsson and Eklundh, 2002). Time series data can also be used to make an improved land cover classification (Cardille and Fortin, 2016; Crowley et al., 2019), as compared to using only a single date image.

By using multitemporal satellite data, seasonal change of species-specific spectral properties can be utilized for making a more accurate tree species classification (Immitzer et al., 2019; Persson, Lindberg, and Reese, 2018; Puletti, Chianucci, and Castaldi, 2018). Nevertheless, the studies done on this have primarily used a small number of satellite images that are cloud-free. In an operational setting, where one might want to continuously improve and update the species classification, a method where missing data is gracefully handled is needed.

1.1.3 Airborne Laser Scanning

The LiDAR sensors of airborne laser scanning (ALS) systems use one or several lasers to make measurements. These work by emitting pulses of light and then measuring the timing and intensity of the echo that the pulse produces when reflected from some surface in the distance (Lindberg, 2012; Maltamo, Næsset, and Vauhkonen, 2014). By making these measurements while keeping track of the sensor's position, the direction of the light pulse, and the time-of-flight, coordinates for the reflecting surface can be produced. The coordinates are known as *points*, *returns*, or *echoes*. A point, because it's a point coordinate in three-dimensional space. A return, because it's light that is returning to the sensor. An echo, because in reality, the pulse has a duration and a footprint, making it possible to record several echoes from a pulse. The duration of the pulse is just the time that the laser shines; it's the duration of the signal sent out. The return signal will probably be more complex than the emitted signal, with a varying intensity that depends on what the light has interacted with. Each peak in such a return signal can be interpreted as an echo. Similar to that of a handheld torch, the light emitted by the laser forms a cone, that is quantified by the beam divergence. At the ground, the pulse will reflect from an approximately circular area, that is the footprint of the pulse. Let's imagine, for a moment, that the light falls on a tree. The first few leaves of that tree will not be so large as to reflect all light in the footprint, resulting in a weak reflection at first. If the light hits a larger group of leaves that all grow at a similar height, then we will get a stronger return signal from that area. Finally, the remaining light might hit the ground and a strong reflection of the light that is left is returned to the sensor.

These measurements create what is known as a *point cloud* with several coordinates produced by a very high frequency of measurements. Together, these coordinates describes the structure of the vegetation and the shape of the terrain. Efforts have been made to make accurate tree species classification from these structural data as well, by looking at both the shape and the structure of tree crowns (Holmgren and Persson, 2004; Maltamo, Næsset, and Vauhkonen, 2014).

Many studies have focused on different properties in the structure of the point cloud to estimate forest properties (Næsset et al., 2004). This is often done using different height *percentiles*. The percentiles describe the shape of a distribution, just like quartiles but there's 100 of them. A large spruce is very good at letting photons in and then utilizing as many as possible for photosynthesis. Nevertheless, some photons of the ones emitted by the ALS system do reflect back from surfaces below the canopy cover. These can then be measured by the ALS sensor, and by looking at different features that describe the height distribution of the returns, we can describe the structure and density of the vegetation.

Depending on the parameters of a data-gathering campaign, ALS data can be produced with different levels of point densities, which might affect whether or not ITC methods are feasible. Area-based methods work well for estimating aggregate measures that might be of interest for forest management (Næsset et al., 2004), such as average height or standing volume but have not proven to be as effective at estimating tree-specific properties such as species (White et al., 2016). When using ITC methods, tree species classification can be made by looking at the surface shape and structure of the tree crown (Lindberg et al., 2014; Vauhkonen et al., 2009; White et al., 2016).

Since the effect of the return signal from the laser pulse is measured, the surface reflectance can be estimated (Kukkonen et al., 2019). The reflectance estimation is more accurate for first and only echoes of a laser pulse (Wagner et al., 2008), and intensity features of first returns have been used for tree species classification (Lindberg, Holmgren, and Olsson, 2021; Lindberg et al., 2014) while others have used intensity features from all returns (Holmgren and Persson, 2004). Until fairly recently, all available ALS systems used only a single wavelength of light, but new developments have allowed for MSALS systems that use several lasers that emit different wavelengths of light. Data from MSALS systems have been used for tree species classification of individual trees based on structural and intensity features with promising results (Ahokas et al., 2016; Budei et al., 2017; Yu et al., 2017). An ALS system can be seen as a form of active aerial imaging (Brandtberg, 2007), and using this analogy, going from a monospectral ALS system to a multispectral one would be similar to going from black-and-white photography to color.

There are also ALS systems that can provide what is known as full-waveform data. These provide, instead of discrete return coordinates, a waveform of the intensity of the return signal. Such data has also been used to classify tree species (Lindberg et al., 2014; Reitberger, Krzystek, and Stilla, 2008) Finally, there are also Single Photon LiDAR (SPL) systems that may allow for a more efficient data collection by providing a denser point cloud when flown at the same height. However, a study on the tree species classification accuracy when using data from such a system has shown that it performs worse than both MSALS systems as well as ordinary monospectral systems (Prieur et al., 2021).

When the surface reflectances have been estimated, there is an interesting opportunity to classify tree species, not only from the average intensity from an area, as is usually done when using passive-optical sensors, but by using the return intensity from specific parts of the tree.

1.2 A Note on Artificial Intelligence and Machine Learning

A recent development in the area of classification is the increased use of machine learning (ML) and artificial intelligence (AI) methods. Even though I've used Random Forest, that is often categorized as an ML method, I've chosen not to focus on the use of these methods. Nevertheless, I would like to write a few words on this, since I've many times got questions about whether or not I've focused on these tools, and especially about why I haven't. First, we need to define what we're talking about, since many times you can see both the AI and ML terms being used very colloquially.

Before the concept of AI was established, there was talk about *machine intelligence*, and Alan Turing published his famous paper where he introduced the Turing Test and the Imitation Game (Turing, 1950). Within this context, a machine intelligence (or AI) would behave in the same way as a human and be indistinguishable from a human in it's responses in a conversation. Machine learning, on the other hand, deals with how machines can be programmed to *learn* something. In the well-cited paper of Arthur Samuel he shows that a machine can learn how to play checkers better than the person programming the computer could (Samuel, 1959). Nowadays, a common view on the difference between ML and statistics is summarized by Bzdok, Altman, and Krzywinski: "Statistics draws population inferences from a sample, and machine learning finds generalizable predictive patterns." (Bzdok, Altman, and Krzywinski, 2018).

As can be seen in Alan Turing's paper, being published in a journal of psychology and philosophy, AI draws closer to the theory and philosophy of mind, rather than modelling. An AI consists of models, true, but is it itself a model? Is human intelligence a model? In the field of AI research, where efforts are made to develop artificial intelligence, there are several subfields, including ML, formal logic, planning and perception (Russell et al., 2022). I find that AI is not as much a tool as it is a concept. Some solutions to problems within the AI field can be very useful to those wishing to classifying tree species (Kattenborn et al., 2021), but "using AI to classify tree species" is not a very precise endeavor. Now I will leave the AI concept and instead write a bit on ML, since it's more of interest to the intrepid remote sensing researcher.

From the name (and Arthur Samuel's paper), it's clear that ML is all about getting machines to learn. In this context, learning is some kind of pattern recognition, and that is also mirrored in the quote from Bzdok, Altman, and Krzywinski. The key words in this quote are *inference* and *sample*, terms that should not be used lightly. With sample, statisticians usually mean that elements have been chosen from a set with a probability, this makes inference possible, that is to draw conclusions or predict properties of the population with some certainty. The probabilities propagate through the statistical computations. In ML, this is not necessary, and maybe not even of interest. All that is of interest for teaching a machine something is to provide a way for it to recognize a pattern. If ML methods are used for classification, it's only possible to say how well the model manages to explain the data it has been trained on and how correct it is when given new data to process. One can not say anything about any population parameter, such as average or spread of some property. Nevertheless, many of the methods used in ML can also be used in a statistical manner, with the probabilities intact. There is a lot of overlap between ML and statistical learning in the algorithms that are used, and the main difference that I can find is how highly formal treatment of probabilities is valued within each field (compare Efron and Hastie, 2021; Hastie, Tibshirani, and Friedman, 2009; Marsland, 2015; Russell et al., 2022).

Methods and algorithms within ML are often designed for very large amounts of data. This is good, because they are designed to find patterns where any human would struggle to get an overview. However, the drawback is that they often also need very large amounts of data to avoid such issues as overfitting. When using remote sensing data, we're in two worlds of data availability. There are huge amounts of data available from sensors mounted to satellites, aircraft, and so on, but not nearly as much reference data from field inventory campaigns. The problems due to a lack of large amounts of reference data can be circumvented by using parametric methods, where we make assumptions on population properties, for example that residuals have a constant variance around a certain model.

Personally, I think that the methods, be they part of ML or statistics, are not what's really interesting in remote sensing research. Instead, I've chosen to focus on research questions concerning what characteristics of remote sensing data that best reflect the forest properties of interest and why that is so. By answering those questions, we can provide feedback to those designing both sensors, platforms and Earth observation missions. In this way we can achieve a more appropriate data collection for, among other things, tree species classification.

1.3 How the Papers Came About

The idea for paper I started to form when I attended a lecture with the then head of research and development at the Swedish forest company Stora Enso, who held a lecture on the use of ALS in forestry. He mentioned something about the NIR reflectance of tree species in ALS data. After his presentation, I had questions about multispectral ALS-data but there had not been any research in that area. This was a very timely question because when I talked with the professor of forest remote sensing, Håkan Olsson, who later became my supervisor, they had just ordered data to be collected using one of the first available MSALS sensors: Optech Titan-X.

Paper II was started by an idea that Håkan Olsson had: he wanted to utilize the repeated observations available in the form of multitemporal satellite imagery to improve tree species classification accuracies. For this paper, the plan was to use a hidden Markov model (HMM) to estimate tree species composition of forests using readily available satellite imagery from the Sentinel-2 mission. An HMM is essentially a Markov chain of state changes that are hidden from observation, but we can measure it indirectly. A Markov chain describes a sequence of changes from one state to another with a certain probability. The classical example that often is given is weather.

Say that we start with a rainy day. The next day the weather might stay the same with a certain probability, change to sunshine or change to cloudy. That is, the weather is changing state. If it's raining right now, it might be more probable that it will rain or be cloudy tomorrow. If it instead had been sunny today, it might be less probable that it will rain tomorrow. So the probability of the weather of tomorrow depends on what weather we have today. These probabilities are what we call a Markov model.

So, what's the *hidden* part? Well, this means that the Markov chain is hidden. In the weather example, that would be like sitting in an office with no windows to observe the weather directly through. Nevertheless, we can observe what clothes people are wearing. If someone passes the office wearing a rain coat, we might say that it's probably raining but it could also be cloudy. It could even be sunny outside, but that's not very probable. In the HMM, in addition to the probabilities of state change, we also have the probabilities of making a particular observation given a state.

The challenge with HMMs is that we need to estimate these probabilities. If we can't, then we don't have a model. So what should our states be? We could say that the state is the tree species on the ground but then state change would very seldomly occur. We could make a separate model for each tree species, with states such as no leaves, leaf out, leaved and senescence, and then choose species by seeing which model fits the best. However, to do that, we need a good model per species for the phenological changes. We need to know the probability that oaks in a particular area are leafing at the fifth of May. Unfortunately, there are no such models available covering the whole of Sweden (that was our area of interest) but I would find it very interesting to see one.

So where did this leave me and my co-authors for the second paper? Strahler (1980) suggested that a Bayesian method for handling prior probabilities could be used with "time-sequential information in making the outcome of a later classification contingent on an earlier classification." This method could easily be combined with maximum likelihood classification, and Swain (1978) wrote a very nice book on, among other areas, this classification method. These were the seeds for paper II in this thesis.

The idea for paper III came from Mats Nilsson, one of my supervisors. He mainly works with environmental monitoring and wanted to see if the Bayesian method for tree species classification could be used for that. Giovanni D'Amico visited SLU in Umeå as a part of his PhD studies, and got to work with applying the method on a larger area. He carried the main load for creating the paper, I only assisted with theory on the method, writing and some example code.

When producing paper I, the idea was already discussed between me and my supervisors to make a similar study in combination with automatically delineated tree crowns. For paper IV we did just that. We tested a more operationally realistic scenario where the labor intensive manual crown delineation that I made for paper I was automated.

2 Goal and Objectives

The main goal of this thesis was to explore how recent developments in remote sensing technology could be used to achieve a more accurate tree species mapping. To do that, I was allowed a great freedom in choosing research questions, data sources and methods to use. To achieve the goal, the main question that I wanted to answer was: "Where can we find more information on tree species in remote sensing data?" It ended up with four papers on tree species classification, of which two are studies utilizing multispectral airborne laser scanning data, and two are studies where multitemporal satellite imagery from the Sentinel-2 mission were used.

2.1 Paper I

The objective of this paper was to explore the properties of MSALS data. To do this, we wanted to answer what features of data that contained most information on tree species, how spectral and structural features compared, and what feature combinations that produced the highest classification accuracy. This was done by defining new features through slicing the point cloud into layers in different ways to see where most information on tree species could be gathered. To these layer features, some additional features, commonly used in combination with ALS data, were also added. At the time, this type of sensor was very new, and not much research had been made on MSALS data for tree species classification purposes.

2.2 Paper II

In this paper, my co-authors and I aimed to utilize remote sensing data from a satellite system that frequently revisits an area to produce a higher tree species classification accuracy. The questions asked were if a Bayesian view on repeat measurements could be useful when handling a stream of data that, beside high-quality images, also contained images partly or completely covered by clouds. We chose to work with Sentinel-2 data, since they have a very dense temporal resolution, with new images taken every 2 to 3 days over Sweden. The key merit of the method presented is its capability to produce an accurate classification despite some or parts of the images being noisy. We used *all* available images, even those completely covered by clouds, to produce a tree species map. We also evaluated the effect on classification accuracy when images with high class separation were selected for use in the Bayesian classification approach.

2.3 Paper III

To further evaluate the results of paper II, this paper was produced where the Bayesian inference method is compared to a RF method for the classification of tree species. The question was how well the Bayesian inference method would perform at a larger scale, where data from the National Forest Inventory (NFI) was used as reference data. We also evaluated how well the Bayesian inference and RF methods for classification performed in forest with different levels of homogeneity and with different number of classes.

2.4 Paper IV

With the features developed for paper I performing fairly well, we wanted to see how they would do in a more realistic scenario. Here we evaluated the performance of different features of MSALS data for tree species classification of closed-canopy forest stands. We used an ITC method where we first automatically delineated the tree crowns and then computed per-tree features that were used for tree species classification.

3 Data

In the papers that are included in this thesis, we have used data from two types of sensors. In papers II and III, we used multitemporal optical satellite imagery from the Sentinel-2 mission, and in papers I and IV, we used MSALS data from two different systems, the Optech Titan-X and the Riegl VQ-1560i-DW.

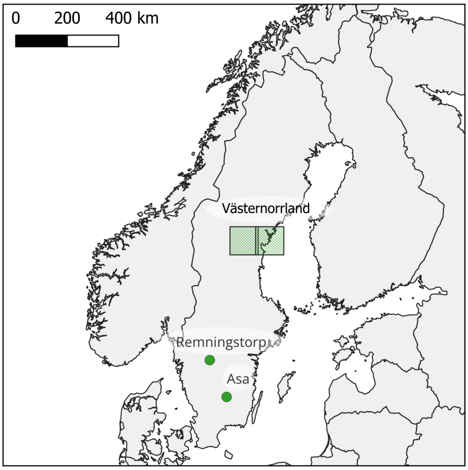

Figure 1: Study areas

The study areas, shown in Figure 1, were located in the boreal and hemiboreal zones of Sweden, in Remningstorp (58°27′18.35″ N, 13°39′8.03″ E; papers I and II), Västernorrland (62°37′18.66″ N, 17°2′40.63″ E; paper III), and Asa (57°10′ N, 14°47′ E; paper IV). The study area of Remningstorp consists of a forest property a bit northeast of Skara in southwestern Sweden and a nature conservation area right next to the property. The landscape consists of broken terrain left by the edge of the icesheet that moved back and forth over the area at the end of the last ice age. The forest property is managed for wood production purposes and is mainly covered by pine (*Pinus sylvestris*) and spruce (*Picea abies*), with some deciduous trees, mainly birch (*Betula spp.*), occurring here and there. In the nature reserve, oak (*Quercus robur*) dominates much of the grazing lands where cows keep the landscape open.

Västernorrland is a region in the middle of Sweden that stretches from the coast to approximately a third of the distance to the western border. This region is similarly diverse in it’s land use as the rest of Sweden. This landscape mainly consists of forest land, with pine, spruce, and birch being the most common tree species, comprising more than 90 % of standing wood volume. In the coastal region, between Örnsköldsvik and Härnösand, lies the UNESCO World Heritage site of Höga kusten. This is an area with several small mountains just by the coast, which is unusual for Sweden.

Asa is an experimental forest in Kronoberg county in southern Sweden. Despite the low latitude, it features a bit harsher climate than surrounding regions. This is due to the higher elevation making early and late frostnights much more frequent. The forest here mainly consists of pine, spruce and birch, but some other deciduous tree species are also present, such as oak. Similarly to Remningstorp, most of the forest is managed for wood volume production, but there are also some grazing grounds dominated by deciduous tree species close to the lake.

3.1 Satellite Imagery

The Sentinel-2 mission for Earth observation consists of two satellites. Both are carrying a multispectral instrument with push-broom sensors. This means that the sensor measures the values of a row of pixels at a time and continuously scans Earth's surface. It provides 13 spectral bands, where each band measures light in a part of the optical spectrum. Not all spectral bands were deemed of interest for tree species classification, such as band 1 that, with a GSD of 60 m and a sensitivity center at 443 nm, provides data on aerosols present in the atmosphere. In paper II we used the green, red and NIR bands, while in paper III, we used nine spectral bands: blue, green, red, three red-edge bands, NIR, and two short-wave infrared (SWIR) bands. To utilize bands with different GSD for paper III, we resampled the bands with a 10 m resolution to match the 20 m resolution of the more coarse bands. The pixels that the Sentinel-2 satellites produce are grouped into *granules*, that is what we can call a "satellite image".

In paper II, we used a total of 142 satellite images from granule 33VVE captured during the period of 2016-07-31 to 2018-08-30. Even though full granules were downloaded and processed, the actual research area where sample plots had been inventoried was small, at around 8.5 by 6 kilometers. The field inventoried plots contained several different tree species, but some were so uncommon that there were too few plots to make any estimations of distributions. The field plots used were each dominated by one of four species: pine (*Pinus sylvestris*), spruce (*Picea abies*), birch (*Betula spp.*), or oak (*Quercus robur*).

For paper III, we used 45 images from the 33VWK and 33VXK granules captured during the months between May and November in the period of 2018 to 2019. The total area of the granules was around 20 000 km^2, with NFI plots throughout the entire area. As for tree species classes, several different ways of partitioning the field data set into classes were examined. For the different partitions, we also excluded plots by varying limit for the heterogeneity that was allowed for a plot to be included in a certain class.

Of note is that during the year 2018, the summer was extremely dry, and that can have affected the separability between species. Remote sensing data from this year is included in both studies. In paper III, we used data from a much larger area than what was used in paper II. This means that while atmospherical variation might have been smaller for measurements used in paper II, they might have been larger for data used in paper III, especially since the research area of paper III included coastline.

3.2 Multispectral Laser Scanning Data

In paper I, the data came from the Optech Titan-X system, that provided data in three different wavelengths, 1550 nm (SWIR), 1064 nm (NIR), and 532 nm (green). The measurements were made at an average altitude of 400 m. The Optech system provided a point density with an average of 10 returns per square meter for each wavelength. The intensity of these returns needed to be calibrated to estimate the surface reflectance. This was done using the radar equation, which scales the value by the square of the distance. In paper I, we included individual trees into the field data by the virtue of their well defined and free-standing crowns and delineated them manually. This was done to produce a data set containing fully grown and well-developed trees that exhibited the properties of their tree species well.

In paper IV, we used data from the Riegl VQ-1560i-DW, that uses only the NIR and green wavelengths. This system kan be flown at a higher altitude than the one used for paper I, and the average flight altitude during data gathering was 800 m. The Riegl system produced data with an average point density of 26.5 returns per square meter for each wavelength. The sensor had been calibrated by Riegl at the factory and used a look-up-table to convert return intensities and distances to a surface reflectance estimation. In paper IV, we wanted to look at how the same features that were used in paper I could be used to classify trees in a closed-canopy forest. For this, we delineated tree crowns automatically by using the ALS data (Holmgren et al., 2022). The field data for paper IV consisted of circular field plots where each tree in the plots had been positioned relative to the plot center.

The only processing of the used point clouds was height normalization. For paper I, the normalization of the point cloud was made using the Digital Elevation Model (DEM) produced by the Swedish Land Survey (Lantmäteriet). This DEM comes in the form of a raster with a spatial resolution of 1 m and has been created using ALS data with a return density of 0.5 to 1.0 returns per square meter. In paper IV, we used the points classified as ground returns in the data from the MSALS system to produce a DEM with a spatial resolution of 0.5 m.

4 Tools and Methods

In my opinion, the most interesting part of research are the research questions and the efforts to answer them. Depending on the research question, what method that is used might be more or less of interest. Personally, I prefer simple statistical models. Even though they might provide lower classification accuracy for a certain case, they might explain some relationship in a way that is easier to comprehend. For this reason, the models I've used in my papers are just that: simple. Advanced methods can definitely perform very well in classification scenarios, but for the questions that I've asked, I did not find them necessary. I wanted to evaluate the use of certain remote sensing data for tree species classification purposes. For example, in paper I, we used LDA, which is a fairly straight forward method. It makes certain assumptions about data, that might or might not be completely true (e.g., we assume homoscedasticity), but to evaluate whether or not a more accurate tree species classification can be made by adding multispectral intensity information, it does just fine.

In the papers in this thesis, we've used an area-based approach in papers II and III, while in papers I and IV we've used ITC methods. This was due to the data used. With data from the Sentinel-2 mission, we could only use area-based methods because each pixel represents an aggregate measurement. Nonetheless, in papers I and IV, the ALS data had such a spatial resolution that ITC methods were very well within our reach.

In my work on the papers in this thesis, I've chosen to only use FOSS. The methods I have used have been implemented in and using tools, among others and in no particular order, like Python, Bash, AWK, GNU Parallel, C, R, and Grass GIS. My effort has been that every calculation should be possible to do by hand or by making a new implementation using a programming language and operating system of choice. To that end, all systems and libraries should be available for anyone to inspect and criticize.

4.1 Bayesian Inference for Multitemporal Satellite Imagery

For paper II, we landed upon a Bayesian description of the flow of probabilities when handling time series data. This method was later also used in paper III. What we really wanted to do was to find the probability $\Pr(\omega_k \mid X_1 \cap X_2 \cap \cdots \cap X_n)$, where ω_k was a class of a pixel, for example pine, spruce or birch, and X_t was an observation made by a Sentinel-2 satellite at time t. That is, the probability of a tree species given a number of observations. We did this by starting with Bayes's theorem,

$$\Pr(A \mid B) = \frac{\Pr(B \mid A)\Pr(A)}{\Pr(B)}. \tag{1}$$

We say that ω_k is the event that the pixel is of class k and X_t is the event of observing the vector $\vec{x}_t$ of band values in the pixel of an image taken at time t. The posterior probability when using the first observation, X_1, is

$$\Pr(\omega_k \mid X_1) = \frac{\Pr(X_1 \mid \omega_k)\Pr(\omega_k)}{\Pr(X_1)}. \tag{2}$$

Using both the first and second observation results in the posterior probability

$$\Pr(\omega_k \mid X_1 \cap X_2) = \frac{\Pr(X_1 \cap X_2 \mid \omega_k)\Pr(\omega_k)}{\Pr(X_1 \cap X_2)} \tag{3}$$

$$= \frac{\Pr(X_2 \mid X_1 \cap \omega_k)\Pr(X_1 \mid \omega_k)\Pr(\omega_k)}{\Pr(X_1 \cap X_2)}. \tag{4}$$

An assumption was made, that observations are conditionally independent given a species, so that

$$\Pr(X_1 \cap X_2 \mid \omega_k) = \Pr(X_1 \mid \omega_k)\Pr(X_2 \mid \omega_k), \tag{5}$$

giving

$$\Pr(X_2 \mid X_1 \cap \omega_k) = \Pr(X_2 \mid \omega_k), \tag{6}$$

allowing for Equation 4 to be written as

$$\Pr(\omega_k \mid X_1 \cap X_2) = \frac{\Pr(X_2 \mid \omega_k)\Pr(X_1 \mid \omega_k)\Pr(\omega_k)}{\Pr(X_1 \cap X_2)}. \tag{7}$$

The denominator in this fraction is a constant irrespective of k, meaning that it can be ignored for classification purposes (Swain, 1978, p. 154). The probabilities can be replaced with the class specific probability density function (Canty, 2019, p. 58). This gives

$$\Pr(\omega_k \mid X_1 \cap X_2) \propto p\left(X_2, \vec{\theta}_{k,2}\right) p\left(X_1, \vec{\theta}_{k,1}\right) \Pr(\omega_k), \tag{8}$$

where p is the probability density function, $\vec{\theta}_{k,t}$ is the parameter vector of that function for species k and image t. In the general case, this is

$$\begin{aligned}\Pr(\omega_k \mid X_1 \cap X_2 \cap \cdots \cap X_n) \propto \\ p\left(X_n, \vec{\theta}_{k,n}\right) p\left(X_{n-1}, \vec{\theta}_{k,n-1}\right) \ldots p\left(X_1, \vec{\theta}_{k,1}\right) \Pr(\omega_k).\end{aligned} \tag{9}$$

A logarithmic transformation does not change the classification result (Swain, 1978, p. 154) and allows for more efficient computation. The selection rule, equivalent to the probability of interest, which was used for classification was: *Select k to maximize*

$$\ln\left(\Pr\left(\omega_k\right)\right)+\sum_{t=1}^{n}\ln\left(p\left(X_t,\vec{\theta}_{k,t}\right)\right). \tag{10}$$

So it all boils down to this last equation that we applied to each pixel value of the satellite data. Of course, the distributions needed to be estimated and we did that by fitting them to reference data for every class and image separately. This equation was implemented in a C program to calculate the probabilities for each pixel, and maximum likelihood was then used to make a species classification for each pixel. Note that the probability can be updated using the same method as new observations are added.

I wanted to present this Bayesian method that we used in papers II and III in full, since, to the best of my knowledge, this method has not been used before for tree species classification using multitemporal data. In paper III, we wanted to evaluate the method at a more operational scale. For comparison, we also used a RF model. A Random Forest classifier is a non-parametric model that does not make assumptions on any distributions of data that it aims to model. It is a forest of de-correlated decision trees that are averaged to make for a model similar to the *k*NN-classifier (Hastie, Tibshirani, and Friedman, 2009).

4.2 Classifying Species of Tree Crowns in Multispectral Laser Scanning Data

In papers I and IV, we wanted to explore what parts of the tree crown that provides most information on tree species when looking at MSALS data. To do this, we extracted features from the tree crowns and tested different subsets of them in a classification model. Apart from using the common features from height and intensity of the ALS data (i.e., percentiles, vegetation ratio, standard deviations and other properties of distributions), we extracted points from certain parts of the point cloud pertinent to the tree crown. This was done by constructing layers (shown in Figure 2), and within each of these layers, some structural and spectral features were calculated. Two kinds of layers were defined: the first type was like those of a cake, with horizontal layers, the other kind was more like the layers of an onion, with ellipsoidal layers, where each layer envelops the ones further inside.

In paper I, we used a stepwise feature selection to find what features that worked well for tree species classification using an LDA. By using the layer

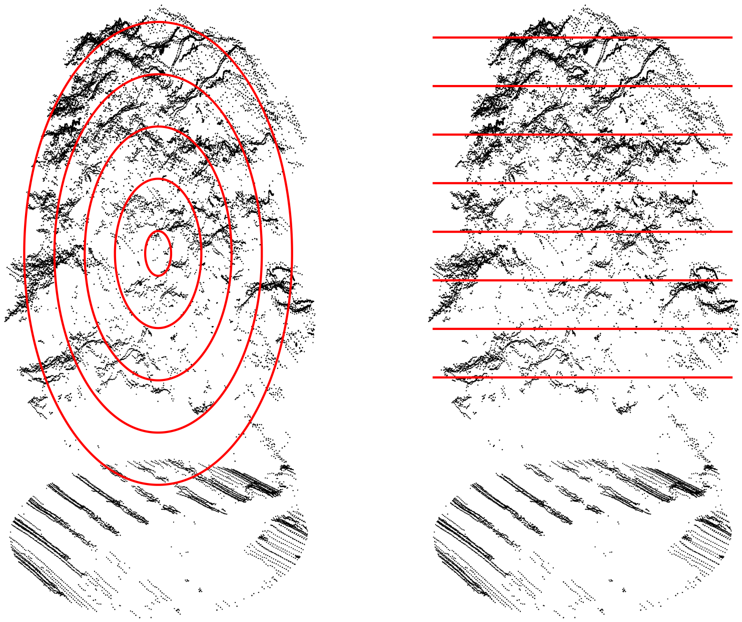

Figure 2: The different types of layers in a tree crown.

features, we could establish where in the tree crown that the best information on tree species could be found. In paper IV, we also used a stepwise feature selection, but this time we opted to use a Quadratic Discriminant Analysis (QDA) for classification but a RF algorithm was also used to examine feature importance.

5 Results and Discussion

Two main conclusions can be drawn from the four papers included in this thesis. The first is that Bayesian methods for updating probabilities as new observations are made provides an opportunity to automate the addition of satellite images for an updated classification. The second is that the multispectral capabilities of modern ALS sensors provide opportunities for a more accurate tree species classification than what can be achieved using monospectral systems, and that the most important parts of this multispectral data are those from the upper and outer parts of the tree crowns.

Results of Paper I In paper I, we found that intensity features of MSALS data carried more information on tree species than what the structural features did. This agrees with the experience from aerial photography interpretation (Ihse, Rafstedt, and Wastenson, 1993) and what others have found when using similar data (St-Onge and Budei, 2015; Yu et al., 2017). Our study also suggested that data from the upper parts of the tree crown provides a better basis for tree species classification than those from further down the canopy. This also agrees with what others have found (Koenig and Höfle, 2016). In this paper, we found that the green laser provided the least information on tree species as compared to the other wavelengths used. Data from the green laser of the Optech Titan-X platform has performed poorly in other studies too (Yu et al., 2017).

Results of Paper II In paper II, we demonstrated that a Bayesian inference, like that suggested by Strahler (1980), was useful for handling large amounts of optical satellite data. We also examined a simple way of ranking satellite imagery by using class separability of reference data. This ranking worked well in combination with the Bayesian method. The inclusion of images with some or complete cloud cover *did* affect the classification accuracy, but it still remained high, at an overall accuracy of 85 % compared to 87 % achieved when only highly ranked images were used. This shows the robustness of the Bayesian method. The overall classification accuracy is in line with previous attempts at tree species classification using data from the Sentinel-2 mission (Ma et al., 2021; Persson, Lindberg, and Reese, 2018; Puletti, Chianucci, and Castaldi, 2018; Wessel, Brandmeier, and Tiede, 2018).

Results of Paper III By comparing the Bayesian method, which is a parametric method, to that of RF, which is a non-parametric method, we showed that they deliver comparable classification results. For more homogeneous forests, the

Bayesian approach performed better than RF and only in scenarios with *mixed*-classes and a high allowance for species heterogeneity within the field data used, did RF perform better. These results were achieved when using data from a much larger study area than that used in paper II.

Results of Paper IV At an operational scale, an automatic tree crown segmentation is needed to allow ITC methods to be used. In paper IV, we examined how the results from paper I could be translated to a closed-canopy forest where tree crown segmentation was done automatically, rather than using manually delineated tree crowns of free-standing trees. We showed that the inclusion of intensity features to the classification model increased overall classification accuracy. Contrary to the findings in paper I, The largest improvement was achieved when intensity features of returns from the green laser were included in addition to the NIR and structural features. The most marked improvement from this inclusion was in the separability of the birch class (*Betula spp.*).

5.1 Classification Using Multitemporal Satellite Imagery

The result in paper III was that the overall accuracy for the Bayesian inference was at a similar level as in paper II. However, for some forest types, RF resulted in a higher classification accuracy. The differences between RF and the Bayesian inference method provides an explanation as to why this could be expected. Random Forest is a non-parametric method, this means that we do not make prior assumptions about population parameters such as the mean and spread. On the other hand, the Bayesian inference method is based on several assumptions. In paper III, we assumed that the spectral features of different species would follow normal distributions. We also assumed that the only variable affecting the difference in spectral features would be the class of trees in that pixel. Mixed classes can possibly violate these assumptions. There could, for example, be a multi-modality in the spectral features of such a class, so that it does not fit very well to a normal distribution. A limitation of the Bayesian inference model that I've proposed is that it assumes discrete classes. However, it might be possible to generalize it to a continuous case with tree species proportions.

The classification of pixels made with the Bayesian method does not provide a good basis for estimating tree species composition of a landscape. Say that we have a pixel where the class probabilities show that we are 34 % sure that it belongs to the pine class, 33 % that it belongs to the spruce class, and 33 % that it belongs to the birch class. In this case we will classify it as pine, even though it could almost as well be spruce or birch. We can't use the likelihoods for estimating species composition either. The only thing that these percentages tells us is that, if we had to guess, we would guess pine.

5.2 Tree Crowns Properties From Multispectral Laser Scanning Data

The properties of ALS data from the same system are more variable than data from the same passive-optical satellite-borne sensor. Different data collection flights may be made at different flight altitudes and flight speeds, with different scan angles. These are factors that affect, among other things, the footprint and point cloud density. Even though papers I and IV use data from different ALS systems, both results are in agreement: intensity features of MSALS gives new opportunities for tree species classification. These results are also in agreement with other studies, where intensity features have been shown to increase tree species classification accuracy (Yu et al., 2017).

The main difference between paper I and IV was the more operational scenario of paper IV. The reference data of paper I and IV were diametric in what they represented. For paper I, field data was gathered by visiting the study area and actively searching for trees of interest. There was no probability sample made. The goal was to find trees that could be seen as typical for their species just to see how they differed in remote sensing data. In contrast, the field inventory data used in paper IV was collected in circular field plots laid out in a grid with a random origin. This was a random sample, and therefore the resulting classification accuracies presented in paper IV should be closer to what can be expected in an operational setting.

The main differences between the results of papers I and IV were that data from the green (532 nm) laser performed poorly in paper I but very well in paper IV. The two systems, Optech Titan-X and Riegl VQ-1560i-DW, are quite different. They are designed for different flight altitudes and thus have different beam divergences and output effects. The data gathering was also made at different altitudes and to different specifications. The differing results seen regarding the green laser shows that they are not generalizable to all MSALS systema. The results also indicate, however, that it might become possible to make a large-scale inventory using MSALS in the future, since these sensors will most likely keep improving.

The different layer features constructed for paper I did not perform very well in paper IV. This discrepancy in performance of the layer features may be explained by the field data used. In paper I, we used a set of free-standing trees chosen specifically for their well-developed crowns, while in paper IV, the tree crowns were not free-standing and they could be of very irregular shape.

As a result, the crudely fitted ellipsoidal and cylindrical shapes were perhaps not suitable for including only the returns pertaining to a single tree. The fitted shapes may not have reflected the actual shape of the tree crowns. This could cause returns to end up in the “wrong” layer, causing an effect similar to that of mixed pixels. Another possibility is that it was harder to tune the parameters used for fitting the shapes to the tree crowns, resulting in the method not working as well in a closed-canopy forest. Also, the ALS data from a closed canopy forest is generally dense at the surface of the canopy, with fewer returns further down within the canopy. As a result of this, the layer features may become obsolete since most points are always in the topmost parts of the tree crowns.

5.3 Outlook on The Future

There are a couple of trends within remote sensing that can benefit tree species classification endeavors of the future. Data tends to come in higher and higher resolution, both spectrally (e.g.,hyperspectral cameras and MSALS), spatially (e.g., smaller GSD for satellite-borne and airborne sensors), and temporally (e.g., repeat ALS campaigns and frequent revisits of satellites). The Swedish Land Survey conducted an ALS data gathering campaign covering the whole of Sweden to produce a high-resolution DEM. The data gathered proved to be very useful for large-scale estimation of forest attributes (Nilsson et al., 2017). These data have also been used for the Swedish NFI sampling design to improve estimations by using them as auxiliary information (Grafström et al., 2017). The Government of Sweden and private forestry actors in Sweden have together financed a second national laser scanning to provide up-to-date information (Swedish Forest Agency, 2022). If future national level ALS campaigns are made using MSALS technology, those data may also become cheaper to use. I think that this is the future for large scale forest inventories in Sweden.

Nevertheless, for MSALS to be used for a large scale inventory, some obstacles still remain. The first is that of operating altitude. Currently, aerial photographs are taken for the National Image Provision Programme (conducted by the Swedish Land Survey) at an altitude of between 2500 m to 7400 m (Swedish Land Survey, 2021). The second revision of an ALS campaign covering all forests of Sweden has been conducted at an altitude of around 3000 m (Swedish Land Survey, 2022). For paper I, the data had been gathered at an altitude of 400 m while the maximum altitude for operating the Optech system is 2000 m. The Riegl system was operated at an altitude of 800 m to gather data for paper IV, but has a maximum operational altitude of 2500 m. With these properties, the MSALS systems used in the papers in this thesis are not efficient enough in their data gathering to be used in a national laser scanning campaign.

Spatial resolution of the point cloud (i.e., density) will be lower when the same system is flown at a higher altitude. The resolution of the latest national ALS campaign is around a single return per square meter. As mentioned, for ITC methods to be used, we need several measurements per tree crown. There are new developments in the realm of ALS technology with the emergence of SPL, that can detect very weak return signals consisting of only a couple of photons. These systems can produce a dense point cloud even when flown at a high altitude. Unfortunately, SPL data has not performed as well in tree species classification (Prieur et al., 2021). Nonetheless, the sensor type might improve in coming years. One thing that I find interesting with the photon counting systems is that the concept of return intensity breaks down. Each photon of a given wavelength carries the same amount of energy. So if single photons are counted, all returns will have the same return intensity. That is without range correction, but that operation would not contribute anything.

For ITC methods to be used in all of Sweden, we will, apart from remote sensing data, also need reference data. Fortunately, all trees within the permanent field plots of the Swedish NFI have had their positions recorded. There are also efforts made to position every tree that is harvested (Saukkola et al., 2019). These sources for large amounts of data could be utilized for making local tree species classification models, as is already done with NFI data for biomass estimation (Nilsson et al., 2017). Large amounts of remote sensing data is already a reality, but with the large amount of reference data that can be produced by harvesters, data driven methods, such as those used in ML, can become more feasible. The problem with harvesting data is that it's hardly a representative sample of all forested land (Räty et al., 2023). This would lead to models that can only make accurate estimates of forest of the kind that *is* harvested.

As for optical satellite imagery, tree species classification efforts can be limited by some of the characteristics that these data have. The spatial resolution is not exactly what it can seem to be going by GSD alone. The pixel can contain a measurement of light that comes from outside of its theoretical extent on the ground. This is due to properties of the sensor, geometry, resampling, co-registration, and other factors. Questions have also been raised regarding the future of satellites in general with what is known as the Kessler syndrome. This syndrome describes the cascading increase of space junk in Low Earth Orbit, causing trouble for any satellite, but there are ongoing efforts to alleviate this problem (Kessler and Johnson, 2010).

Freely available satellite imagery is the only optical data that can provide information for the whole of Earth without being affected by local conflicts and wealth inequalities. However, producing reference data for remote and inaccessible areas might prove a challenge. At a global scale, large land cover classes are needed to make the classification easier when reference data is lacking. The extremely high temporal resolution of the Sentinel-2 mission is unique to the satellite platform, making seasonal changes of vegetation observable. If per-species phenological models could be produced for the whole of Sweden, classification by seasonal changes would be even more feasible.

Tree species is a property of an individual tree. If tree species classification is the goal, then ITC methods are the way to go. Unfortunately, the multitemporal data from the Sentinel-2 mission is not of such a quality that ITC methods can be applied. Nevertheless, there have been efforts made to utilize satellite imagery with very high spatial resolution for tree species classification (Wagner et al., 2018). If longer time series of repeat measurements with a high spatial resolution lies in the future, image analysis methods might allow for the creation of even super resolution images. This assumes that the data delivered from those satellites are in a more raw state than that delivered from the Sentinel-2 mission. Multispectral ALS have been proven to be a good data source for tree species classification endeavors, but future systems need to be able to collect very dense data from a high altitude for the sensor to be operationally viable. Medium-resolution satellite data can be of interest when classifying groups of trees, but in that case, a continuous variable, such as tree species proportions, should be used.

But what do I know?

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References

Ahokas, E. et al. (2016). “Towards Automatic Single-Sensor Mapping by Multispectral Airborne Laser Scanning”. In: *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XLI-B3, pp. 155–162. issn: 2194-9034.

Asner, G. P. (1998). “Biophysical and Biochemical Sources of Variability in Canopy Reflectance”. In: *Remote Sensing of Environment* 64.3, pp. 234–253. issn: 00344257.

Brandtberg, T. (2007). “Classifying Individual Tree Species under Leaf-off and Leaf-on Conditions Using Airborne Lidar”. In: *ISPRS Journal of Photogrammetry and Remote Sensing* 61.5, pp. 325–340. issn: 0924-2716.

Breidenbach, J. et al. (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”. In: *Remote Sensing of Environment* 114.4, pp. 911–924. issn: 00344257.

Budei, B. C. et al. (2017). “Identifying the Genus or Species of Individual Trees Using a Three-Wavelength Airborne Lidar System”. In: *Remote Sensing of Environment*. issn: 00344257.

Bzdok, D., Altman, N., and Krzywinski, M. (2018). “Statistics versus Machine Learning”. In: *Nature Methods* 15.4 (4), pp. 233–234. issn: 1548-7105.

Canty, M. J. (2019). *Image Analysis, Classification and Change Detection in Remote Sensing: With Algorithms for Python*. Fourth edition. Boca Raton, FL: CRC Press/Taylor & Francis Group. isbn: 978-1-138-61322-5.

Cardille, J. A. and Fortin, J. A. (2016). “Bayesian Updating of Land-Cover Estimates in a Data-Rich Environment”. In: *Remote Sensing of Environment* 186, pp. 234–249. issn: 00344257.

Crowley, M. A. et al. (2019). “Multi-Sensor, Multi-Scale, Bayesian Data Synthesis for Mapping within-Year Wildfire Progression”. In: *Remote Sensing Letters* 10.3, pp. 302–311. issn: 2150-704X.

Dalponte, M. et al. (2013). “Tree Species Classification in Boreal Forests With Hyperspectral Data”. In: *IEEE Transactions on Geoscience and Remote Sensing* 51.5, pp. 2632–2645.

Deur, M., Gašparović, M., and Balenović, I. (2020). “Tree Species Classification in Mixed Deciduous Forests Using Very High Spatial Resolution Satellite Imagery and Machine Learning Methods”. In: *Remote Sensing* 12.23, p. 3926. issn: 2072-4292.

Efron, B. and Hastie, T. (2021). *Computer Age Statistical Inference: Algorithms, Evidence, and Data Science*. Student edition. Institute of Mathematical Statistics Monographs 6. Cambridge, United Kingdom New York, USA Port Melbourne, Australia New Delhi, India Singapore: Cambridge University Press. 491 pp. isbn: 978-1-108-82341-8.

Elifrits, C. D., Barr, J., and Johannsen, C. J. (1978). “Mapping Land Cover From Satellite Images: A Basic, Low Cost Approach”. In: NASA Contractor Report 2952.

Eva Lindberg et al. (n.d.). *Tree Species Classification in Boreal Forests from Remote Sensing - next Generation Forest Maps in Sweden for Ecology and Management*. Unpublished. Swedish University of Agricultural Sciences.

Fassnacht, F. E. et al. (2016). “Review of Studies on Tree Species Classification from Remotely Sensed Data”. In: *Remote Sensing of Environment* 186, pp. 64–87. issn: 00344257.

Fassnacht, F. E. et al. (2022). “About the Link between Biodiversity and Spectral Variation”. In: *Applied Vegetation Science* 25.1, e12643. issn: 1654-109X.

Gillespie, T. W. et al. (2009). “Towards Quantifying Tropical Tree Species Richness in Tropical Forests”. In: *International Journal of Remote Sensing* 30.6, pp. 1629–1634. issn: 0143-1161.

Gini, R. et al. (2012). “Aerial Images from an Uav System: 3d Modeling and Tree Species Classification in a Park Area”. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XXXIX-B1, pp. 361–366. issn: 1682-1750.

Goodbody, T. R. H., Coops, N. C., and White, J. C. (2019). “Digital Aerial Photogrammetry for Updating Area-Based Forest Inventories: A Review of Opportunities, Challenges, and Future Directions”. In: *Current Forestry Reports* 5.2, pp. 55–75. issn: 2198-6436.

Grafström, A. et al. (2017). “A New Sampling Strategy for Forest Inventories Applied to the Temporary Clusters of the Swedish National Forest Inventory”. In: *Canadian Journal of Forest Research* 47.9, pp. 1161–1167. issn: 0045-5067, 1208-6037.

Hastie, T., Tibshirani, R., and Friedman, J. H. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. 2nd ed. Springer Series in Statistics. New York, NY: Springer. 745 pp. isbn: 978-0-387-84857-0.

Holmgren, J. and Persson, Å. (2004). “Identifying Species of Individual Trees Using Airborne Laser Scanner”. In: *Remote Sensing of Environment* 90.4, pp. 415–423.

Holmgren, J. et al. (2022). “Tree Crown Segmentation in Three Dimensions Using Density Models Derived from Airborne Laser Scanning”. In: *International Journal of Remote Sensing* 43.1, pp. 299–329. issn: 0143-1161, 1366-5901.

Hovi, A., Raitio, P., and Rautiainen, M. (2017). “A Spectral Analysis of 25 Boreal Tree Species”. In: *Silva Fennica* 51.4. issn: 22424075.

Ihse, M., Rafstedt, T., and Wastenson, L. (1993). “Flygbildstolkning av vegetation”. In: *Flygbildsteknik och fjärranalys*. Skogsstyrelsen, p. 430. isbn: 91-884 62-04-8.

Immitzer, M., Atzberger, C., and Koukal, T. (2012). “Tree Species Classification with Random Forest Using Very High Spatial Resolution 8-Band WorldView-2 Satellite Data”. In: *Remote Sensing* 4.9, pp. 2661–2693. issn: 2072-4292.

Immitzer, M. et al. (2019). “Optimal Input Features for Tree Species Classification in Central Europe Based on Multi-Temporal Sentinel-2 Data”. In: *Remote Sensing* 11.22, p. 2599.

Jonsson, P. and Eklundh, L. (2002). “Seasonality Extraction by Function Fitting to Time-Series of Satellite Sensor Data”. In: *IEEE Transactions on Geoscience and Remote Sensing* 40.8, pp. 1824–1832. issn: 0196-2892.

Kangas, A. et al. (2018). “Remote Sensing and Forest Inventories in Nordic Countries – Roadmap for the Future”. In: *Scandinavian Journal of Forest Research* 33.4, pp. 397–412. issn: 0282-7581, 1651-1891.

Kattenborn, T. et al. (2021). “Review on Convolutional Neural Networks (CNN) in Vegetation Remote Sensing”. In: *ISPRS Journal of Photogrammetry and Remote Sensing* 173, pp. 24–49. issn: 0924-2716.

Kessler, D. J. and Johnson, N. L. (2010). “The Kessler Syndrome: Implications to Future Space Operations”. In: 33rd ANNUAL AAS GUIDANCE AND CONTROL CONFERENCE. Breckenridge, Colorado.

Kluczek, M., Zagajewski, B., and Zwijacz-Kozica, T. (2023). “Mountain Tree Species Mapping Using Sentinel-2, PlanetScope, and Airborne HySpex Hyperspectral Imagery”. In: *Remote Sensing* 15.3 (3), p. 844. issn: 2072-4292.

Koenig, K. and Höfle, B. (2016). “Full-Waveform Airborne Laser Scanning in Vegetation Studies—A Review of Point Cloud and Waveform Features for Tree Species Classification”. In: *Forests* 7.9. issn: 1999-4907.

Kukkonen, M. et al. (2019). “Multispectral Airborne LiDAR Data in the Prediction of Boreal Tree Species Composition”. In: *IEEE Transactions on Geoscience and Remote Sensing* 57.6, pp. 3462–3471. issn: 0196-2892, 1558-0644.

Lillesand, T. M., Kiefer, R. W., and Chipman, J. W. (2007). *Remote Sensing and Image Interpretation*. 6th ed. John Wiley & Sons. isbn: 81-265-3223-8.

Lin, Y. and Herold, M. (2016). “Tree Species Classification Based on Explicit Tree Structure Feature Parameters Derived from Static Terrestrial Laser Scanning Data”. In: *Agricultural and Forest Meteorology* 216, pp. 105–114.

Lindberg, E. (2012). “Estimation of Canopy Structure and Individual Trees from Laser Scanning Data”.

Lindberg, E. and Holmgren, J. (2017). “Individual Tree Crown Methods for 3D Data from Remote Sensing”. In: *Current Forestry Reports* 3.1, pp. 19–31. issn: 2198-6436.

Lindberg, E., Holmgren, J., and Olsson, H. (2021). “Classification of Tree Species Classes in a Hemi-Boreal Forest from Multispectral Airborne Laser Scanning Data Using a Mini Raster Cell Method”. In: *International Journal of Applied Earth Observation and Geoinformation* 100, p. 102334. issn: 15698432.

Lindberg, E. et al. (2010). “Estimation of Tree Lists from Airborne Laser Scanning by Combining Single-Tree and Area-Based Methods”. In: *International Journal of Remote Sensing* 31.5, pp. 1175–1192. issn: 0143-1161, 1366-5901.

Lindberg, E. et al. (2014). “Delineation of Tree Crowns and Tree Species Classification From Full-Waveform Airborne Laser Scanning Data Using 3-D Ellipsoidal Clustering”. In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 7 (7, SI), pp. 3174–3181. issn: 1939-1404.

Ma, M. et al. (2021). “Tree Species Classification Based on Sentinel-2 Imagery and Random Forest Classifier in the Eastern Regions of the Qilian Mountains”. In: *Forests* 12.12 (12), p. 1736. issn: 1999-4907.

Maltamo, M., Næsset, E., and Vauhkonen, J., eds. (2014). *Forestry Applications of Airborne Laser Scanning: Concepts and Case Studies*. Managing Forest Ecosystems 27. Dordrecht: Springer. 464 pp. isbn: 978-94-017-8662-1.

Marsland, S. (2015). *Machine Learning: An Algorithmic Perspective*. Second edition. Boca Raton, FL: CRC Press. isbn: 978-1-4665-8333-7.

Matikainen, L., Hyyppä, J., and Litkey, P. (2016). “Multispectral Airborne Laser Scanning for Automated Map Updating”. In: *ISPRS – International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XLI-B3, pp. 323–330.

Næsset, E. and Bjerknes, K.-O. (2001). “Estimating Tree Heights and Number of Stems in Young Forest Stands Using Airborne Laser Scanner Data”. In: *Remote Sensing of Environment* 78.3, pp. 328–340. issn: 00344257.

Næsset, E. et al. (2004). “Laser Scanning of Forest Resources: The Nordic Experience”. In: *Scandinavian Journal of Forest Research* 19, pp. 482–499.

Nilsson, M. et al. (2017). “A Nationwide Forest Attribute Map of Sweden Predicted Using Airborne Laser Scanning Data and Field Data from the National Forest Inventory”. In: *Remote Sensing of Environment* 194, pp. 447–454. issn: 00344257.

St-Onge, B. and Budei, C. (2015). “Individual Tree Species Identification Using the Multispectral Return Intensities of the Optech Titan Lidar System”. In: *Proceedings of SilviLaser 2015*. La Grande Motte, France, pp. 71–73.

Persson, H. J., Olofsson, K., and Holmgren, J. (2022). “Two-Phase Forest Inventory Using Very-High-Resolution Laser Scanning”. In: *Remote Sensing of Environment* 271, p. 112909. issn: 00344257.

Persson, M., Lindberg, E., and Reese, H. (2018). “Tree Species Classification with Multi-Temporal Sentinel-2 Data”. In: *Remote Sensing* 10.11, p. 1794. issn: 2072-4292.

Prieur, J.-F. et al. (2021). “A Comparison of Three Airborne Laser Scanner Types for Species Identification of Individual Trees”. In: *Sensors* 22.1, p. 35. issn: 1424-8220.

Puletti, N., Chianucci, F., and Castaldi, C. (2018). “Use of Sentinel-2 for Forest Classification in Mediterranean Environments”. In: *Annals of Silvicultural Research* 42.1. issn: 2284-354X.

Puliti, S. et al. (2017). “Assessing 3D Point Clouds from Aerial Photographs for Species-Specific Forest Inventories”. In: *Scandinavian Journal of Forest Research* 32.1, pp. 68–79. issn: 0282-7581, 1651-1891.

Qin, H. et al. (2022). “Individual Tree Segmentation and Tree Species Classification in Subtropical Broadleaf Forests Using UAV-based LiDAR, Hyperspectral, and Ultrahigh-Resolution RGB Data”. In: *Remote Sensing of Environment* 280, p. 113143. issn: 0034-4257.

Rahlf, J. et al. (2015). “Forest Parameter Prediction Using an Image-Based Point Cloud: A Comparison of Semi-ITC with ABA”. In: *Forests* 6.12, pp. 4059–4071. issn: 1999-4907.

Räty, J. et al. (2023). “Assessing and Mitigating Systematic Errors in Forest Attribute Maps Utilizing Harvester and Airborne Laser Scanning Data”. In: *Canadian Journal of Forest Research* 53.4, pp. 284–301. issn: 0045-5067, 1208-6037.

Reitberger, J., Krzystek, P., and Stilla, U. (2008). “Analysis of Full Waveform LIDAR Data for the Classification of Deciduous and Coniferous Trees”. In: *International Journal of Remote Sensing* 29.5, pp. 1407–1431. issn: 0143-1161, 1366-5901.

Russell, S. J. et al. (2022). *Artificial Intelligence: A Modern Approach*. Fourth edition, global edition. Pearson Series in Artificial Intelligence. Harlow: Pearson. 1166 pp. isbn: 978-1-292-40113-3.

Samuel, A. L. (1959). “Some Studies in Machine Learning Using the Game of Checkers”. In: *IBM Journal of Research and Development* 3.3, pp. 210–229. issn: 0018-8646, 0018-8646.

Saukkola, A. et al. (2019). “Predicting Forest Inventory Attributes Using Airborne Laser Scanning, Aerial Imagery, and Harvester Data”. In: *Remote Sensing* 11.7, p. 797. issn: 2072-4292.

Strahler, A. H. (1980). “The Use of Prior Probabilities in Maximum Likelihood Classification of Remotely Sensed Data”. In: *Remote Sensing of Environment* 10.2, pp. 135–163. issn: 00344257.

Swain, P. H. (1978). “Fundamentals of Pattern Recognition in Remote Sensing”. In: *Remote Sensing; The Quantative Approach*. McGraw–Hill International Book Company, pp. 136–187. isbn: 0-07-062576-X.

Swedish Forest Agency (2022). *Ökad punkttäthet vid nationell laserskanning*. Kunskapsunderlag, kunskapssammanställning 2022-19.

Swedish Land Survey (2021). *Digital Aerial Photographs*. Product decription.

— (2022). *Laser Data*. Quality description.

Turing, A. M. (1950). “I.—COMPUTING MACHINERY AND INTELLIGENCE”. In: *Mind* LIX.236, pp. 433–460. issn: 1460-2113, 0026-4423.

Vauhkonen, J. et al. (2009). “Identification of Scandinavian Commercial Species of Individual Trees from Airborne Laser Scanning Data Using Alpha Shape Metrics”. In: *Forest Science* 55.1, pp. 37–47. issn: 0015749X.

Wagner, F. H. et al. (2018). “Individual Tree Crown Delineation in a Highly Diverse Tropical Forest Using Very High Resolution Satellite Images”. In: *ISPRS Journal of Photogrammetry and Remote Sensing* 145, pp. 362–377. issn: 09242716.

Wagner, W. et al. (2008). “3D Vegetation Mapping Using Small-Footprint Full-Waveform Airborne Laser Scanners”. In: *International Journal of Remote Sensing* 29.5, pp. 1433–1452.

Wessel, M., Brandmeier, M., and Tiede, D. (2018). “Evaluation of Different Machine Learning Algorithms for Scalable Classification of Tree Types and Tree Species Based on Sentinel-2 Data”. In: *Remote Sensing* 10.9, p. 1419. issn: 2072-4292.

White, J. C. et al. (2016). “Remote Sensing Technologies for Enhancing Forest Inventories: A Review”. In: *Canadian Journal of Remote Sensing* 42.5, pp. 619–641. issn: 0703-8992, 1712-7971.

Wollersheim, M., Collins, M. J., and Leckie, D. (2011). “Estimating Boreal Forest Species Type with Airborne Polarimetric Synthetic Aperture Radar”. In: *International Journal of Remote Sensing* 32.9, pp. 2481–2505. issn: 0143-1161.

Yang, Z. et al. (2023). “Forest Tree Species Diversity Mapping Using ICESat-2/ATLAS with GF-1/PMS Imagery”. In: *Forests* 14.8 (8), p. 1537. issn: 1999-4907.

Yu, X. et al. (2017). “Single-Sensor Solution to Tree Species Classification Using Multispectral Airborne Laser Scanning”. In: *Remote Sensing* 9.2, p. 108. issn: 2072-4292.